3-2018

# Affective Computing for Emotion Detection using Vision and Wearable Sensors

Alphonsus Keary
*Department of Computer Science, Cork Institute of Technology, Bishopstown, Cork.*

# Affective Computing for Emotion Detection using Vision and Wearable Sensors

| | |
|---|---|
| **Volumes:** | **Volume 1 of 2** |
| **Author:** | **Alphonsus Keary, MSc** |
| **Award:** | **This thesis is submitted as the fulfilment of the requirement for the award of the degree of Doctor of Philosophy** |
| **Department:** | **Computer Science** |
| **Supervisors:** | **Prof Paul Walsh (CIT)**<br>**Dr Kieran Delaney (CIT)**<br>**Prof Matthias Hemmje (FTK)** |

**Submitted to the Cork Institute of Technology, (03) (2018)**

# Author’s Formal Declaration

I hereby state that this thesis submission document is entirely my own work except where otherwise accredited.

This thesis has not been submitted for an award at any other institution.

| | |
|---|---|
| ____________________________ | ______________________ |
| **Alphonsus Keary** | **Date** |
| ____________________________ | ______________________ |
| **Prof Paul Walsh (CIT)** | **Date** |
| ____________________________ | ______________________ |
| **Dr Kieran Delaney (CIT)** | **Date** |
| ____________________________ | ______________________ |
| **Prof Matthias Hemmje (FTK)** | **Date** |

# Thesis Abstract Volume 1 of 2


**Affective Computing for Emotion Detection using**

**Vision and Wearable Sensors.**

The research explores the opportunities, challenges, limitations, and presents advancements in *computing that relates to, arises from, or deliberately influences emotions* (Picard, 1997).

The field is referred to as Affective Computing (AC) and is expected to play a major role in the engineering and development of computationally and cognitively intelligent systems, processors and applications in the future.

Today the field of AC is bolstered by the emergence of multiple sources of affective data and is fuelled on by developments under various Internet of Things (IoTs) projects and the fusion potential of multiple sensory affective data streams.

The core focus of this thesis involves investigation into whether the sensitivity and specificity (predictive performance) of AC, based on the fusion of multi-sensor data streams, is fit for purpose? Can such AC powered technologies and techniques truly deliver increasingly accurate emotion predictions of subjects in the real world?

The thesis begins by presenting a number of research justifications and AC research questions that are used to formulate the original thesis hypothesis and thesis objectives. As part of the research conducted, a detailed state of the art investigations explored many aspects of AC from both a scientific and technological perspective. The complexity of AC as a multi-sensor, multi-modality, data fusion problem unfolded during the state of the art research and

this ultimately led to novel thinking and origination in the form of the creation of an AC conceptualised architecture that will act as a practical and theoretical foundation for the engineering of future AC platforms and solutions. The AC conceptual architecture developed as a result of this research, was applied to the engineering of a series of software artifacts that were combined to create a prototypical AC multi-sensor platform known as the Emotion Fusion Server (EFS) to be used in the thesis hypothesis AC experimentation phases of the research.

The thesis research used the EFS platform to conduct a detailed series of AC experiments to investigate if the fusion of multiple sensory sources of affective data from sensory devices can significantly increase the accuracy of emotion prediction by computationally intelligent means. The research involved conducting numerous controlled experiments along with the statistical analysis of the performance of sensors for the purposes of AC, the findings of which serve to assess the feasibility of AC in various domains and points to future directions for the AC field.

The AC experiments data investigations conducted in relation to the thesis hypothesis used applied statistical methods and techniques, and the results, analytics and evaluations are presented throughout the two thesis research volumes. The thesis concludes by providing a detailed set of formal findings, conclusions and decisions in relation to the overarching research hypothesis on the sensitivity and specificity of the fusion of vision and wearables sensor modalities and offers foresights and guidance into the many problems, challenges and projections for the AC field into the future.

## Thesis Table of Contents

## Thesis List of Figures

## Thesis List of Tables

## Thesis Acknowledgements

This thesis research is a direct result of the CIT Rísam PhD Scholarship Programme[1] and CIT financial support in gratefully acknowledged. My extreme thanks and appreciation goes to my main thesis supervisor, Prof Paul Walsh (CIT), who through ingenious motivation ensured I kept on the road to make this thesis deliverable a reality. Many thanks also to my second supervisor, Dr Kieran Delaney (CIT), who provided an extremely relevant practical and project oriented focus to this research. Special thanks also goes to my third supervisor, Prof Matthias Hemmje (FTK), who brought a methodological approach and direction to ensure that the work was progressed, integrated and applied both from an academic and practical perspective. My deepest gratitude goes to all of my three PhD supervisors for their professional support throughout.

I would also like to thank the following at CIT. Dr Tim Horgan, for his support and understanding. Andrea O'Driscoll, for her exceptional professional support at the graduate research office. Dr Niall Smith (CIT Research) and Hannah Petersson (ISU) for their support during the International Space University (ISU) programme at CIT. Conor O'Neill for organisation and access to research facilities.

Very special acknowledgement and thanks goes to Dr Catherine Palmer for her guidance and direction in statistical evaluations relating to this research. Also thank you to Dr Sean Lacey for his highly informed and relevant lectures on statistic methods and techniques.

Special thanks goes to the following SIGMA researchers. Dr Timothy Manning for his inspiration, direction, motivation and deep insights into machine learning.

[1] http://www.cit.ie/prospectivestudents/postgraduates/risam/

Xiang Lu fellow researcher for his advice and direction. Michael Healy and Ryan Donovan fellow researchers working on AC related projects. Also special thanks to Dr. Cintia Palu, Suzanne Considine, Mark Roddy, and Dr. Prasad Gade. I would also like to thank Dr. Brian Kelly (NSilico) for his motivation and direction throughout.

Special acknowledgement and recognition goes to two international students from Brazil, Leonardo Mesquita da Silva and Igor Pessoa who contributed to early stage AC prototypes and who also worked on various aspects of the Emotion Fusion Server code base. Also I would like to thank Robin Spiteri for his on-going support and discussions on R based data extraction tools and techniques for AC research.

The AC experiments involved thirty three individuals that committed a serious amount of their time to this research. My sincere thank you and appreciation goes to all those who participated and assisted with this novel AC research.

This research would not have been possible without the endless love and support of my family. Thank you to our children Ian, Daryn and Leanne for helping me through what has at times seemed like an endless journey.

Finally, there is one person alone that has truly made this thesis research happen. To my wife Mary, thank you so much for your genuine support, your go-for-it attitude, and your endless love, throughout a momentous and life changing number of years.

Mary, this research is dedicated to you!

## Thesis Index

# 1 Thesis Introduction, Motivation, Hypothesis and Objectives

Considering current and projected technological innovations and data volumes (Ramakrishnan & Kumar, 2016), (Marr, 2016) there is a sound justification and demand for systems that are capable of working with more cognitive-aware, human-like and naturalistic features. Recent decades have seen the amalgamation of technologies (computing and telecommunications) and the development of cloud computing, data analytics, Machine Learning (ML) (Mitchell, 1997), High Performance Computing (HPC) (Kunze, Joubert, & Grandinetti, 2015), and new forms of processors and memory technologies (Castelvecchi, 2017). There are now ever increasing expectations of a major paradigm shift with a consequential impact on work, business, governments, and society brought on by the emergence of computationally and cognitively intelligent systems, processors and applications (IBM, 2017).

This research was undertaken at the Centre for Software Innovation and Machine Intelligence Applications known as SIGMA (SIGMA - Cork Institute of Technology (CIT), 2016) at the Cork Institute of Technology (CIT) (Cork Institute of Technology, 2017). The central research hypothesis of this thesis (discussed formally in later sections of this chapter) aims to explore the potential opportunities, challenges, limitations and advancements of Affective Computing (AC) (Oxford Dictionaries, 2017) science and technology with specific focus on the performance and capabilities of both vision and wearable sensory technologies.

The nascent, evolving and multifaceted field of AC primarily studies and develops computational techniques for the monitoring and analysis of emotional and cognitive states in humans. This multifaceted nature of the field is reflected by increasing influences from other traditional fields such as computing, psychology, electrical and signal engineering, physiology, social science, medicine, neurology, and bioinformatics. Rosalind Picard is accredited as a founder of the field and defines AC as *computing that relates to, arises from, or deliberately influences emotions* (Picard, 1997), [p. 3].

The direction and development of this thesis has been shaped by early stage research into the application and potential of AC in Games Based Learning (GBL) (Keary, Walsh, O'Byrne, Moizer, & Lean, 2013), the Quantified Self (QS) field (The Economist, 2012) (Keary & Walsh, 2014), stress management, and most specifically healthcare. Initial AC healthcare related research helped produce a successful research proposal called SenseCare (Sensory Enabled Affective Computing for Enhancing Medical Care) (SenseCare Consortium, 2016) which subsequently won formal EU funding.

## 1.1 Research Motivation, Direction and Justification

The section provides a background to the research conducted and acts as foundational input to the reasoning behind the thesis hypothesis to be presented in this chapter. It presents a short review of the motivation, direction and justification for the AC research along with discussion on relevant and related application domains that will be impacted by the outcomes of this thesis research in the future.

### 1.1.1 Games Based Learning Research

Ng et al. in (Ng, Khong, & Thwaites, 2012) explain how Human Computer Interaction (HCI) (Dictionary.com, 2017) aspects of *affective gaming has been gaining ground as more game developers and the HCI community recognize the importance of emotion in games*, [p. 689]. Their paper discusses affective design which they see as a critical issue and challenge in future games development. New thinking and engineering is required in affective integration and this will result in more *mixed-methodologies and multi-disciplinary approaches*, [p. 690] to game design in the future. Yannakakis et al. agree and see the need to *focus at establishing protocols for the integration of emotion research in the pipeline of game production* (Yannakakis, Isbister, Paiva, & Karpouzis, 2014), [p. 2] along with the need for linkages across multiple research fields in order to advance and create innovations in affective gaming.

With reference to online gaming platforms, they see the rich data sets of player activity as an extremely valuable resource that could be harvested for the determination of analytical relationships between *detailed player metrics, and cognitive and affective maps of [gaming] experience* (Yannakakis, Isbister, Paiva, & Karpouzis, 2014), [p. 2]. GBL and other gaming systems are entering an era where real-time human affect can be integrated into the design and overall experience. According to (Yannakakis, Isbister, Paiva, & Karpouzis, 2014), [p. 2], in order to maintain the growth trajectory of the GBL sector, along with AC integration, affect needs to be engineered in the design and production phases of games development. Also players may be rewarded or penalised based on affective states such as happiness, aggression, anger, stress, etc. achieved in a game. These affective computing engineering developments can be expected to meet with strict ethical, security, and regulatory challenges in the future.

As part of this programme of PhD research, early stage contributions have been made to the S-Cube 3D multi-player virtual worlds GBL platform (Asperges, et al., 2014) and the ENACT psychosocial communications skills online training platform (ENACT Consortium, 2015) EU research projects. Research conducted included an AC architecture proposal for S-Cube and a software prototype AC vision interface for the ENACT project. Further discussions on both of these GBL research projects can be found in chapter two.

### 1.1.2 Emotional Stress and Quantified Self Research

Work spans all sectors and numerous challenges and opportunities exists in relation to the European Framework Directive 89/391 (European Commission, 1989) where employers have a legal responsibility to reduce risks to workers' health and safety stemming from work-related emotional stress and psychosocial conditions (mental illness, depression). Figures from the European Agency for Safety and Health at Work (European Agency for Safety and Health at Work, 2014) estimates put annual work related stress financial costs to be in the region of €25.4 billion (figures based on EU-15 member states).

The field of psychoneuroimmunology (PNI) (Newman, 2016) considers work related emotional and physiological stress as one of the major influencers on ones quality of life, work capabilities, mental health, and physical well-being. In (Newman, 2016), Newman explains how *managing levels of stress can help maximise the virility of your immune system* thus having a direct quantifiable impact on human health and working lives.

The QS movement (Live Science, 2017) and its related developments and technologies also has a direct relationship and contribution to make to human stress emotional management and control. Research work carried out in relation to stress and QS (Keary & Walsh, 2014) discussed how AC research could heavily influence the field of QS. In their paper, the authors argue that the future focus for QS should not be solely on biometric signal processing and that there is a justification for the union of the fields of AC and QS with the research into PNI as one of the key scientific drivers for their claim.

Given the above factors and evidence there is a justified need and demand for practical work-based solutions that can provide support to employees, employers, governments, and associated bodies in dealing with work and occupation related stressful situations and activities. Call centre stress recognition research by Hernandez et al. (Hernandez, Morris, & Picard, 2011), developments into affective user interfaces for transportation (Hernandez, et al., 2014) and the thesis hypothesis related AC scientific experiments conducted for this research are all contributions to the challenge of creating affective cognitively engineered stress-aware workplaces, interfaces and systems in the future.

### 1.1.3 Healthcare and Medical Informatics Research

Today healthcare and medical informatics terminology incorporates eHealth (Car, Tan, Huang, Sloot, & Franklin, 2017) and other terms such as connected health (Skiba, 2015), mHealth (Kumar & et al., 2013) and medtech (AusMedtech 2016, 2016). For the purpose of clarity throughout this thesis, the *eHealth* term will be used and will incorporate the many other terms in use today relating to distributed and connected healthcare processes and medical informatics technologies.

One of the topics regularly highlighted in the literature is eHealth integration with AC research (Luneski, Konstantinidis, & Bamidis, 2010), (Mertz, 2016), (Brunet-Gouet, Oker, Martin, Grynszpan, & Jackson, 2015). Across eHealth there are a wide range of challenges and opportunities for affective applications. For example, in dementia care alone, Alzheimer Disease International estimates that there are approximately 30 million people inflicted with dementia across the world. This is predicted to increase to 100 million by 2050 and excludes the millions involved in professional and home care (Wimo & Prince, 2010) services. The economic burden of dementia ranks higher than stroke, heart disease and cancers combined. In 2009, the total worldwide societal cost of dementia, was estimated to be $422 billion (Alzheimer Europe, 2009). The integration of affective systems into healthcare has the potential for significant financial and productivity gains with patients, carers, and medical professionals having insights into physical, affective, and cognitive states.

With reference to this thesis, research conducted into AC and eHealth resulted in the compilation of an academic and industry research consortium that encompassed expertise in AC, ML, big data fusion, psychology, medical informatics, and dementia care. Very much driven by the potential of AC across the eHealth domain, the SenseCare proposal was prepared on behalf of the consortium with the author of this thesis (under the supervision of Prof Paul Walsh) as one of the lead proposal authors. The SenseCare proposal was submitted to the EU commission Horizon 2020 - Marie Skłodowska Curie Actions - Research and Innovation Staff Exchange (H2020-MSCA-RISE-2015) (EU Commission, 2017) call. Following an extensive review by the EU commission and an independent panel of industry experts, the SenseCare proposal successfully secured funding from 2016 to 2019 under grant agreement number 690862. Chapter two provides a more detailed overview of the SenseCare project and its AC related functionality.

### 1.1.4 Gartner International Research

This section now moves to a higher level of abstraction and presents the Gartner Hype Cycle (GHC) (Gartner, 2017) which is a useful analytics tools for the evaluation and projection of emerging technologies. The GHC in Figure 1-1 Gartner Hype Cycle for Emerging Technologies 2016 also provides an international perspective on the ripeness of AC for exploitation across multiple technologies and various application domains in the future.

The GHC version assessed the maturity, business benefit, and future direction of more than 2,000 technologies (Gartner, 2016), (Maheshwari, 2016). Three significant technological trends were identified by Gartner and key emerging technologies that are interlinked with AC are outlined below.

- **#1 - Transparently immersive experiences**
    - ***AC related technologies:*** *Connected home; Augmented reality; Virtual reality; Human augmentation; Brain Computer Interfaces (BCI)* (Shih, Krusienski, & Wolpaw, 2012) *and Gesture control devices.*
- **#2 - Perceptual smart machine age**
    - ***AC related technologies:*** *Smart dust* (Dorrier, 2016)*; Machine learning; Smart workspaces; Virtual personal assistants; Cognitive expert advisors; Smart robots and Conversational user interfaces.*
- **#3 - Platform revolution**
    - ***AC related technologies:*** *IoTs platforms.*

AC is categorised by Gartner as a transparently immersive experience that is on the rise towards the peak of inflated expectations which could well take between five to ten years. AC is new and exciting and is currently surrounded by excessive hype but the Gartner research is a stark reminder of how long a journey new technologies may take before true integration and productivity across future application domains, organisations, governments, and society.

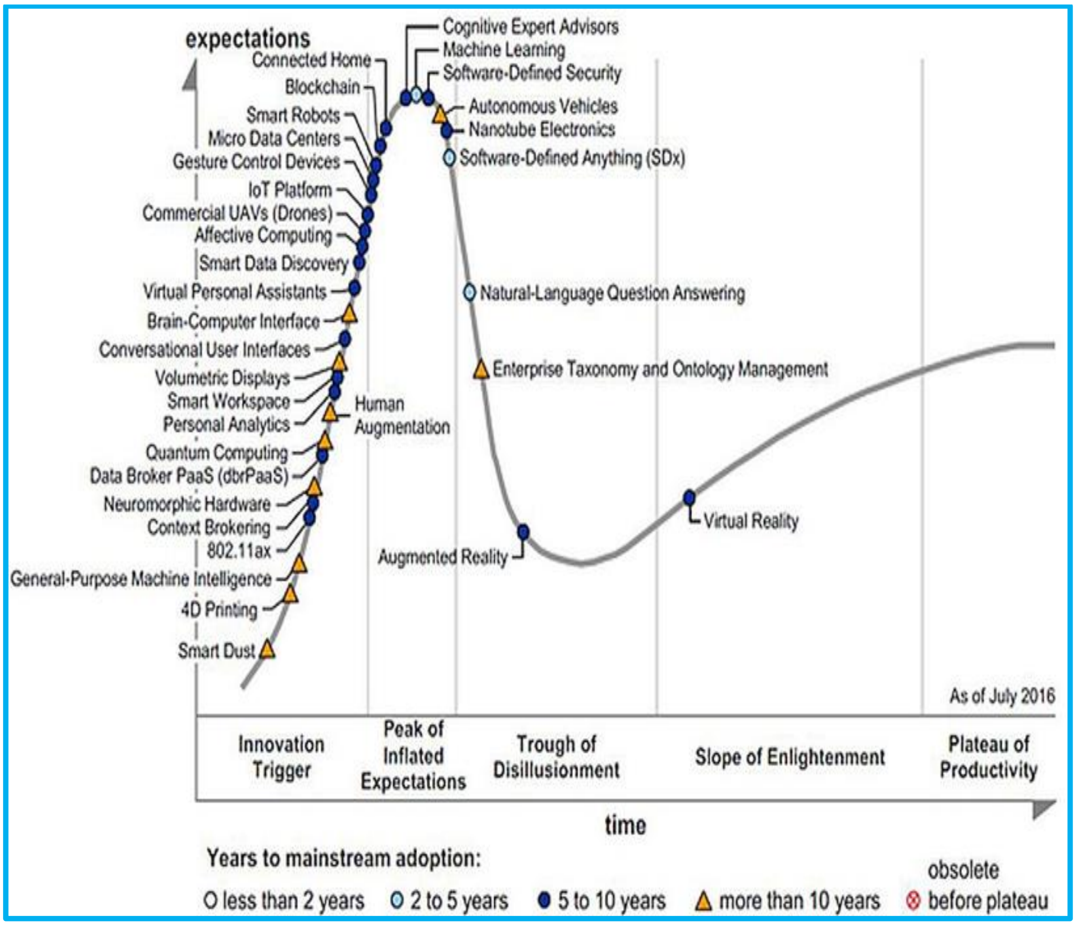



**Figure 1-1 Gartner Hype Cycle for Emerging Technologies 2016 (Gartner, 2016)**

### 1.1.5 Summary

The previous sections have presented an insight into potential application domains for AC and the main motivations, directions, and justifications for the thesis research and hypothesis. The GHC analytics also provided an international context to the discussion and a broader technological scoping in terms of domains and technologies where AC may be applied in the future.

On reflection, and by means of a fitting conclusion to this introductory section, it is important to restate that in recent years there has clearly been a major upsurge in academic and commercial interests/involvement in AC. There is now the most likely prospect that AC expectations are overinflated (considering how much is still unknown about human affect (emotions) (Sukel, 2016), (Wager, Kang, Johnson, Nichols, & Satpute, 2015)) and the field could be in danger of suffering a similar fate experienced by its Artificial Intelligence (AI) (Winston, 1993) parent in the late seventies.

The AI winter is a stark historical reminder of how following a number of AI successes with machines that could mimic humans (Faggella, 2015), the resulting over inflated expectations of AI led to a mass withdrawal of research funding and subsequent devastation for the fledgling AI field at the time. For AC there are considerable problems, challenges, opportunities, and goals that lie ahead. In consideration of the complexity of human affect, cognition, and brain function, and with the lessons learnt from the AI winter of the past, perhaps a strategy of hasten slowly may be pragmatic, as AC scientific and technological research advances into future decades to come.

## 1.2 Overall Problems and Challenges in Affective Computing

From an overarching perspective, this research relates to enabling the development of computational and cognitively intelligent affective systems. In the near term, such AC powered systems will have the potential to be deployed to address a range of the complex problems and challenges such as those outlined below.

- *Development of eHealth and QS systems that offer emotional based support and services to dementia patients, carers and healthcare professionals.*
- *Creation of systems that offer support and understanding to patients with cognitive impairments (depression, addiction, body weight management, autism…) and providing for more informed holistic decisions in relation to their treatment plans.*
- *Creation of intuitive user interfaces that can monitor and manage the stress levels of users and offer advice and interventions if and when required.*
- *Engineering of unobtrusive embedded vehicle/transport user interfaces capable of tracking driver/pilot stress, emotional states and physiological signals.*
- *Creation of innovative learning technologies that can recognise and identify anger, engagement, frustration, confusion, understanding and other learner difficulties and provide additional focused support to learners.*
- *Development of intelligent, user model based, affective computing solutions for serious games.*

The research motivation, direction, and justification described in the previous section is directly related and applicable to a number of the overall problems and challenges outlined above such as dementia care, weight management, autism, QS, stress analytics, driver stress tracking and monitoring, and learning innovations incorporating GBL developments.

Considering the broad spectrum and complexity of the AC field and the overall problems and challenges outlined in this section, at this stage it is important to narrow the scale and scope of the research in order to formalise and outline the thesis hypothesis. With this in mind, the next section limits the research scope via the formulation of a thesis problem statement along with a number of directly related challenges.

## 1.3 Problem Statement and Related Challenges

As discussed this far, AC and cognitive computing (Marr, 2016) powered developments and transformations will ultimately create new paradigms, applications and enterprises over the coming decades (Schatsky, Petrov, & Ronanki, 2015), (Murgia , 2016).

Today the field of AC is bolstered by the emergence of multiple sources of affective data streams. This is fuelled on by developments under various IoTs (European Commission, 2017) research projects and the fusion potential of multiple sensory affective data streams. While there is likely to be on-going debate in relation to the AC reasoning capabilities of individual sensory devices, one of the main challenges today for researchers and developers building AC based systems relates to reliability, trust, ethics, real-world functional capabilities, and accurate *morally acceptable portraits of people* (Cowie, 2015) [p. 334].

With this in mind, the core focus of this thesis is one of AC reliability and accuracy. In statistical analysis, reliability and accuracy are often discussed in relation to the concepts of sensitivity and specificity. In a clinical setting, the *sensitivity of a test (also called the true positive rate) is defined as the proportion of people with the disease who will have a positive result* (Statistics How To, 2018). The higher the sensitivity rate of the test then the more persons that will be identified with the disease. In an AC context, the sensitivity rating could be used to indicate the presence of an emotion state (true positive) in a person. The higher the sensitivity rating then the more likely the emotion is present.

Also in a clinical setting, the *specificity of a test (also called the true negative rate) is the proportion of people without the disease who will have a negative result* (Statistics How To, 2018). The higher the specificity rate of the test then the more persons that will be identified without the disease. Applying this in an AC context, the specificity rating could be used to indicate the non-presence of an emotion state (true negative) in a person. The higher the specificity rating then the more likely the emotion is not present.

With reference to the above explanations, this research is investigating whether the sensitivity and specificity (Sammut & Webb, 2010) of AC, based on the fusion of multi-sensor data streams is fit for purpose. Also it investigates if AC technologies and techniques can truly deliver more accurate and reliable emotion predictions for subjects in the real world? The thesis research addresses these extremely relevant fundamental questions. It will investigate if the fusion of multiple sensory sources of affective data from sensory devices can significantly increase the accuracy of emotion prediction by computationally and statistically intelligent means.

Having now outlined the formal thesis problem statement the following set of directly related research challenges have been concretely defined.

- The psychological side of AC is extremely relevant to the thesis problem statement and will need specific related investigations.

- The scientific, technological, sensor and multi-sensory fusion aspects of AC will require detailed investigations.
- The research should be conducted with a focus and potential around selected AC future application domains and principally eHealth related.
- A prototypical solution incorporating both hardware sensor adaptors and AC related processing capabilities needs to be developed.
- Experiments need to be designed and conducted with reference to the investigation of the sensitivity and specificity of AC.
- Experiment results need to be statistically processed and analysed in order to produce and evaluate the findings and conclusions in relation to the sensitivity and specificity of AC.
- The future directions and remaining challenges of the AC field also need to be investigated in order to define further research directions.

In order to address the high-level thesis problem statement of AC sensory sensitivity and specificity, and the related challenges discussed above, a series of corresponding research questions have been formulated and are logically presented in the next section.

## 1.4 Corresponding Research Questions

The sensitivity and specificity of affective sensors relates to the requirement for increased reliability, accuracy, and confidence in the predictive performance and classification of the emotional and cognitive state of an individual. The following research questions have been practically formulated in relation to the thesis problem statement and its related challenges that were discussed in the previous section.

***RQ1 Are there links between AC and psychology?***

- Selected theories, models and tools from the field of psychology that have had a significant impact on AC must be researched and investigated in order to understand the links across both fields.

***RQ2 What are the scientific aspects of AC?***

- AC is a multi-disciplinary field and there is the need to investigate the more formal scientific aspects of the field that are emerging.

***RQ3 What technology exists for AC research and development?***

- There is a need to research and investigate suitable hardware and software technologies, and solutions that can be used for the engineering and development of AC systems and platforms.

***RQ4 What are the future application domain potentials for AC?***

- Need to conduct further research into the potential of AC in future application domains such as eHealth, stress management, QS and learning (incorporating GBL).

***RQ5 Why is data fusion important and how does it relate to AC and can it increase the sensitivity and specificity of affective states beyond that of any unimodal sensory device?***

- There is a need to research, investigate, and conduct experiments relating to how AC sensors can be fused together to increase the sensitivity and specificity of emotional states beyond that produced by typical unimodal AC sensors.

***RQ6 Can a prototype system be developed for use in multi-modality, fusion based AC experiments?***

- There is a need to research, investigate, conceptualise, engineer, and develop a prototypical AC system to be used for the processing and fusion of multi-modality sensory data.

***RQ7 Can a series of experiments be conducted into the sensitivity and specificity of AC with a focus on vision and wearables modalities?***

- Predictive performance impacts the credibility of various sensors and this must be researched and understood such that sensory devices may be trusted and validated for use in AC systems in the future. Thus, a series of AC vision, wearables and self-report related experiments (using selected hardware adaptors for the prototype software system developed) must be conducted in relation to addressing the thesis problem statement.

***RQ8 What applied statistical methods and techniques are required for the AC experiments?***

- Selection and identification of statistical methods and techniques to be used in the AC fusion based experiment evaluation processes is required.

***RQ9 What are the results and findings of the series of AC experiments conducted from a sensitivity and specificity perspective?***

- AC experiments statistical reporting and evaluations need to be analysed to garner new knowledge and learning for future multi-sensory fusion projects.

***RQ10 What are the future challenges and directions of the AC field?***

- This requires the summation of new knowledge resulting from the thesis research, clarification of any further work that needs to be conducted and insights into the next phases in the development of the AC field.

The previous section has narrowed down the scope of the research into a defined thesis problem statement along with a set of related research challenges. This section has then converted them into a set of specific scientific, theoretical, technological, and practical oriented research questions. The next logical step in this introductory chapter is to define a formal overall thesis hypothesis which is presented in the next section.

## 1.5 Thesis Research Hypothesis

The research questions presented in the previous section are now summarised and formulated into the following overarching formal thesis research hypothesis ($\boldsymbol{H^0}$) with an exclusive focus on AC vision and wearable sensory technologies.

- ***$H^0$*** *- The fusion of affective sensory data from vision analytical systems with multi-sensory physiological analytical systems does not significantly increase the sensitivity and specificity (predictive performance) of emotion recognition when tested on subjects in typical emotionally generated situations or events.*

## 1.6 Thesis Research Objectives

The following defined thesis research objectives (TO) have been formalised and established to align with the research questions and the formal thesis hypothesis (***$H^0$***) presented in the previous sections.

**TO1 Investigate the role of psychology in AC research:**

- Research and investigation into how psychology has influenced the development and links with the AC field.

**TO2 Investigate the scientific aspects of AC literature and research activities:**

- Study AC literature and related research projects to identify the scientific aspects and issues of the field with specific focus on sensor modalities.

**T03 Investigate the range of hardware and software technologies used in AC research:**

- Explore hardware and software technologies available for use in AC research with specific focus on sensor modalities.

**TO4 Conduct research into relevant future AC application domains:**

- Investigation and research into the future AC application domains of eHealth, stress management, QS and learning (incorporating GBL).

**TO5 Research the use of data fusion techniques in current AC multi-modality research:**

- What are the scientific, theoretical, and technological aspects of data fusion and how do they relate to AC research.

**TO6 Conceptualisation and development of a prototypical, multi-modality AC fusion based platform for use in the thesis research experiments:**

- This involves the conceptualisation, engineering, development, and testing of a prototypical software platform, capable of interfacing via defined adaptors with unimodal and multi-modal AC sensory data sources. The platform engineering and design should incorporate the potential for related algorithms to be applied at unimodal and multi-modal levels in a sensory fusion based architecture.

**TO7 Conduct a series of AC experiments related to the thesis hypothesis using the prototypical fusion platform developed in TO6:**

- Specification, design, development, ethical authorisation, and conducting of a series of AC experiments related to the testing of the thesis research hypothesis $\boldsymbol{H^0}$ with a focus towards the future AC application domains to be investigated in T04.

**TO8 Use and application of statistical methods and techniques relating to AC experiments:**

- The preparation, pre-processing, re-structuring, training and testing of datasets generated from AC research experiments in TO7. Investigation and application of relevant statistical methods, tools, algorithms, and techniques to identify, design, and create more cognizant learning and modelling for the prediction of affective and cognitive states in subjects based on multi-sensory fusion potentials.

**TO9 Processing and compilation of AC experiment results, findings and conclusions:**

- Conducting hypothesis related evaluations and conclusions in relation to the AC experiments conducted.

**TO10 Conduct research into the future problems, challenges, and directions of the AC field:**

- Combine informed literature review, experimental results/findings and personal opinion/foresights to present the future problems, challenges and directions of the AC field.

This section presented a full set of research objectives that this thesis aims to achieve and that will be described throughout the remaining chapters. The thesis objectives are also directly correlated with a defined methodological based research approach which is explained in the next section.

## 1.7 Thesis Approach and Methodology

This section presents an overview of two established research methodologies that are of relevance to this research. The Design oriented Information Systems Research methodology (DISR) created by Österle et al. (Österle, et al., 2011) and the Research Framework for Information Systems Research (RFISR) by Nunamaker and Chen (Nunamaker, Chen, & Purdin, 1990). Both methodologies have their individual merits but either one alone does not quite fit with the methodological approach taken in this particular thesis research.

The thesis research conducted has incorporated phases of the DISR involving the analysis, conceptualisation, engineering and development of novel artifacts and has applied elements of the RFISR such as observation, experimentation and also development. In order to apply aspects of both methodologies, it was decided to merge selected phases from the DISR and RFISR to create a hybrid research methodology. Both DISR and RFISR are briefly described below and are followed by a description of the hybrid methodology that was used throughout the research.

**The DISR methodology incorporates the following four phases:**

- **Analysis:** This involves the identification, description and specification of the problem to be researched and incorporates state of the art (SoTA) research and analysis. Following this, a gap analysis is conducted on the identification of the limitations in the existing state of the art in solving the given problem. This leads to a research plan for the development of novel artifacts to address the identified problem(s).
- **Design:** This involves the design and development of the novel artifacts with recognition and justification for the use of any existing solutions in the

design and development process or explanation as to why they would not apply.

- **Evaluation:** Novel artifacts are evaluated against the original specified objectives.
- **Diffusion:** Publication of intermediate and final results of the research.

**The RFISR methodology incorporates the following four phases:**

- **Observation**: This involves case studies, surveys or field research to identify why the research is required.
- **Theory building:** Various methods, techniques, models and frameworks are used to formalise the problem and to create a proposed solution.
- **Systems development:** Prototyping, development or technology transfer activities are carried out in relation to artifacts that can be used in solving the problem.
- **Experimentation:** Conducting a series of experiments on the developed artifacts to confirm their potential in addressing the problem.

As discussed above, a hybrid methodology has been created and applied to this research thesis. The following presents a thesis applied description of seven phases that have been incorporated into the hybrid methodology used which is a combination of selected phases from both the DISR and RFISR.

**The hybrid methodology incorporates the following seven phases:**

- **Observation and problem analysis:** Thesis research plans are defined in relation to the AC research to be conducted. Problem statement is compiled and identified gaps and challenges are outlined. High level research and foresight into AC future application domains is also conducted. Detailed research questions, thesis hypothesis and thesis objectives are defined and formalised.

- **Problem modelling:** Identification of the requirements to conduct SoTA scientific and technological research activities to create a more detailed model and evaluation of the AC gaps, problem and challenges. The thesis hypothesis and objectives are further defined and used as the main driver of the SoTA focus on the sensitivity and specificity of AC multi-sensory fusion.
- **State of the art research:** This is the formal conducting of the SoTA scientific and technological review as part of the problem modelling process. The SoTA review incorporates research into psychology, vision, wearables, other sensor-modalities, sensory fusion, and applied AC future domain related research. It also presents an evaluation of the gaps, problems and challenges facing the AC field in the short and longer term.
- **System design:** Conceptual modelling and design of a prototypical software artifact(s) to be used in addressing the thesis hypothesis experiments phase. This involves the high-level conceptualisation and design which incorporates the proposed architecture, data stream processing, data fusion, algorithmic processes, related hardware, and integrated third party solutions that make up the artifact(s) design.
- **Implementation:** Presents more formal technical hardware and software details in relation to the artifact(s) to be developed and implemented for usage in the experimental and evaluation stages of the research.
- **Experimentation:** Using selected sensory hardware in conjunction with the implemented prototypical solution software artifact(s), a series of AC experiments are conducted. The resulting datasets produced are

processed using statistical evaluation methods and techniques to produce results and findings relating to the formal thesis hypothesis.

- **Conclusions:** Summary of results and findings from the research conducted are published and disseminated throughout and at the concluding stages of the research. Further software development involving the prototypical AC system artifact(s) and where future experimentation may be required is also described. Remaining future problems and challenges are identified along with an updated revisit to the future application domains for AC.

### 1.8 Thesis Structure Overview

This section provides a brief outline of the remaining chapters in the thesis.

Chapter two - State of the Art in Affective Computing Science and Technology: This chapter provides in-depth evidence, direction, future challenges, goals, and discussion on the scientific and technological aspects of AC and Affective Science (AS) (Colombetti, 2014).

Chapter three – Conceptual Modelling and Design: This chapter presents the conceptual modelling and design processes that have been applied in the development of relevant use cases, information modelling of data streams and the sensory fusion aspects of the research. The design and engineering of the conceptual architecture of software artifact(s) relating to a prototypical AC platform is also presented.

Chapter four – Proof of Concept and Implementation: This chapter has a practical focus on the tools and base technological artifact(s) used throughout the research. It also describes the development of the technical software components and services that have been integrated into the prototypical software and hardware artifact(s) used in the various experimental activities.

Chapter five – Evaluation: The focus of this chapter is on the evaluation of the original research hypothesis ($\boldsymbol{H^0}$) via a series of AC experiments that were conducted and supported by the tools, technologies and prototypical software artifact(s) described in chapters three and four. The experimental evaluation methodology, design, specification details, and delivery processes along with detailed results, findings and conclusions are presented here.

Chapter six – Thesis Contributions, Conclusions and Future Work: This chapter summarises the main contributions of the thesis research work and its main findings and conclusions in order to accept or reject the formal thesis hypothesis. This is followed by a highlight section on the potential dangers and threats of AC and other forms of AI related technologies. The future of AC is revisited in relation to further new application domains and the many remaining scientific and technological challenges that exist for the field. The chapter concludes with a discussion on the open issues that have resulted from the thesis research and it also provides updates and directions on future research related activities to be carried out.

## 1.9 Chapter Summary

The first section of chapter one documented the observation and problem analysis phase of the hybrid methodology used. This started with the positioning of the motivation, direction and justification for the research. This was followed by a discussion on a number of overall complex problems and challenges that AC is facing in selected future application domains.

The next section defined the specific thesis problem statement and a set of directly related problems and challenges. This assisted in further defining and narrowing the focus and scope of the research towards the sensitivity and specificity aspects of AC.

Next, in order to address the problem statement and the AC challenges, a collection of corresponding research questions were created. Having outlined the research questions, the next section formalised and produced an overall thesis research hypothesis ($\boldsymbol{H^0}$).

The chapter also documented aspects of the problem modelling phase of the hybrid methodology. This was in the form of the applied modelling of the thesis hypothesis into a definitive set of thesis objectives (TO1 – TO10) that have been defined and documented in this chapter. The methodology section discussed and explained the hybrid approach that was used and applied to the specific phases of the research conducted. Chapter one concluded with an overview of the remaining chapters in the thesis.

# 2 State of the Art in Affective Computing Science and Technology

This chapter specifically addresses research questions one to five and their corresponding thesis objectives presented in chapter one. In particular, the chapter will investigate how psychology influences AC (RQ1 and TO1), what the scientific issues and challenges are, core sensory technologies involved (RQ2, RQ3 and TO2, TO3) and future application domains (RQ4 and TO4) for the AC field. This chapter also investigates the role of multi-sensory data fusion (RQ5 and TO5), applied machine learning techniques used in AC research (RQ2-3 and TO2-3), and other related research.

## 2.1 Affective Computing Overview and Origins

Affective is a term used in relation to personal feelings, emotions, moods, and cognitive states (Merriam-Webster, 2017), (Oxford Dictionaries, 2017). Wilhelm Wundt (Encyclopaedia Britannica, 2012) (recognised as one of the founding figures of experimental psychology) described affect as a fundamental ingredient of the human mind (Feldman-Barrett & Gross, 2013). During the 1980s, affective science (AS) emerged to combine research on *emotions, moods, preferences, attitudes, value, and stress* (Feldman-Barrett & Gross, 2013) under a common scientific domain.

With advances in computing, AC emerged as a natural development and can be seen as a key enabler for the research and theories of AS. AC differs from AS in that it is concerned with the development of computational systems capable of detecting, responding to, and simulating human emotional states (Oxford Dictionaries, 2017). The interdisciplinary nature of AS also applies to AC which today spans computer science, psychology, cognitive science, sociology, physiology, and medical science (Banafa, 2016). Both fields are certainly interrelated and form a cyclical relationship with one another. Today, AC offers an ever increasing array of tools and technologies that can be used in AS, which can then lead to the progression of research and understanding of human emotions and cognition, thus advancing AC futures.

The scientific literature clearly links Picard with the origins of AC. In her book, Picard explains how the work of Manfred Clynes was a major influence on her research (Picard, 1997). Clynes is credited with the development of a machine called a sentograph that was capable of measuring emotion (Clynes, 1977). The sentograph measured slight changes in directional pressure applied to an immovable button that was pushed by an individual. This work by Clynes took place during the 1960s and is an indicator of the more recent origin and potential direction of the AC field. Other noted influences on Picard's work include Damasio (Damasio, 1994), Cytowic (Cytowic, 1996) and Negroponte (Negroponte, 1995).

AC did not just suddenly arise out of the work of any one individual. Indeed there have been many contributors that will be discussed throughout this chapter two. The study of emotion goes back many centuries. For example, the seminal work of Charles Darwin, The Expression of the Emotions in Man and Animals (Darwin, 1872) was published in 1872. At this time, Darwin's thinking and theories were influenced by research into expressions and emotions from disciplines such as philosophy, psychology, physiology, and medicine. In the conclusions to his published work, Darwin wrote that *expression in itself, or the language of the emotions, as it has sometimes been called, is certainly of importance for the welfare of mankind*. *To understand, as far as is possible, the source or origin of the various expressions which may be hourly seen on the faces of the men around us, not to mention our domesticated animals, ought to possess much interest for us* (Darwin-Online.org and Dr John van Wyhe, 2017), [p. 360].

With this historical and extremely pertinent call to action by Darwin, the remaining sections of this chapter investigate the scientific and technological sensor related aspects of AC.

## 2.2 Affective Computing and Psychology

In recent research developments, AC has played a pivotal role in the provision of tools and services that can assist with advancing the research and theories of AS. Correspondingly, AC has harvested the research and theories of AS in advancing computational intelligence and developing new forms of innovative affective and cognitive applications. Due to this synergistic and complementary relationship between AC and AS there is a justified need to investigate the role of psychology (incorporating AS) in AC. AC researchers must have some formal understanding and appreciation of the vital role psychology plays in AC research. This knowledge and understanding of psychology will ultimately play a pivotal role in the formulation of new and innovative algorithms and techniques for AC.

This section opens with the positioning of the role of psychology in AC and is followed by a study of established models of emotion with relevant discussion around identified issues and challenges from the literature. The two remaining sub-sections discuss psychological oriented tools used in conducting AC experiments and the various types of sensory data sources available to provide psychological based emotional insights to AC systems.

### 2.2.1 Role of Psychology in Affective Computing

Common to both AC and AS is psychological science (Sage Publishing, 2017). AS originated as a specialised branch of psychology and today the field has produced dedicated journals such as Emotion Review and Social Cognitive and Affective Neuroscience (Feldman-Barrett & Gross, 2013) and many book publications. AC is relatively new but already there are numerous dedicated books such as the Oxford Handbook of Affective Computing (Calvo, D'Mello, Gratch, & Kappas, 2015) and a specialised journal, IEEE Transactions on Affective Computing (IEEE, 2017) for the field. In keeping with the focus of the thesis research conducted, this section on the role of psychology presents relevant research, theories and tools primarily from an AC perspective.

Reisenzein et al. (Reisenzein, et al., 2013) discuss the complementarity of psychology and computer science to the computational modelling of emotion (AC). Using the work of Strongman (Strongman, 2003) (which lists 150 psychological and philosophical emotion theories), Reisenzein et al. (2013) primarily propose the deconstruction of emotion theories into basic modular assumptions which involves evaluating and reducing well established existing emotion theories into a set of basic assumptions (Reisenzein, et al., 2013). In addition, their research discusses modelling emotions using 1) cognitive architectures such as Soar, ACT-R (Reisenzein, et al., 2013) [p. 258], 2) the Belief Desire Intention (BDI) agent architecture (Reisenzein, et al., 2013) [p. 259] and 3) affective agent architectures such as FatiMA Modular and MAMID

(Reisenzein, et al., 2013) [p. 260]. Overall they argue for the translation of *emotion theories into a common informal conceptual system or a formal language, or (to) implement them in a common architecture* (Reisenzein, et al., 2013), [p. 246].

W3C's recommendation of an emotion markup language, EmotionML (W3C, 2014) and the Artificial Intelligence Markup Language (AIML) (ALICE AI Foundation, 2017) are examples of relevant tools. These tools may be used by researchers for the formalisation of emotional concepts and can assist in advancing the relationship between established theories of emotion and AC. Reisenzein et al. have set out a detailed vision and undoubtedly their proposals will certainly assist computer scientists in understanding and dealing with the evolving complexity of human emotions and cognitive states.

### 2.2.2 Models of Emotions

This section primarily discusses the Circumplex Model of Affect, the Energy/Stress model and the Ortony, Clore and Collins (OCC) Cognitive Model. Current thinking in relation to the modelling of emotions is also discussed.

**Circumplex Model of Affect:** James Russell (1980) describes the Circumplex Model of Affect (Russell, 1980) in Figure 2-1 Russell's Circumplex Model of Affect with reference to the measures of valence and arousal which are highly referenced in the literature. Valence is a measure of positive/negative feelings by a person towards something while arousal relates to the levels of attention exhibited by a person. Valence and arousal (salience) are further explained by Picard (1997) in discussion relating to the limbic system in the brain which is regarded as the seat of emotion, memory, and attention (Picard R. , 1997), [p. 5].

Russell's model presents evidence of how *affective dimensions are interrelated in a highly systematic fashion* (Russell, 1980), [p. 1161]. The model uses the concept of an affective circle starting on the right hand side at 0° for pleasure, 45° excitement, 90° arousal, 135° distress, 180° displeasure, 225° depression, 270° sleepiness and 315° relaxation.

The Circumplex Model of Affect presents valence as opposite extremes of a pleasure scale moving from 0° to 180° where high levels of displeasure may be felt. In contrast, Russell presents the arousal scale on the model as an elated arousal state at 90° that then moves to an acute polar opposite of sleepiness at 270°.

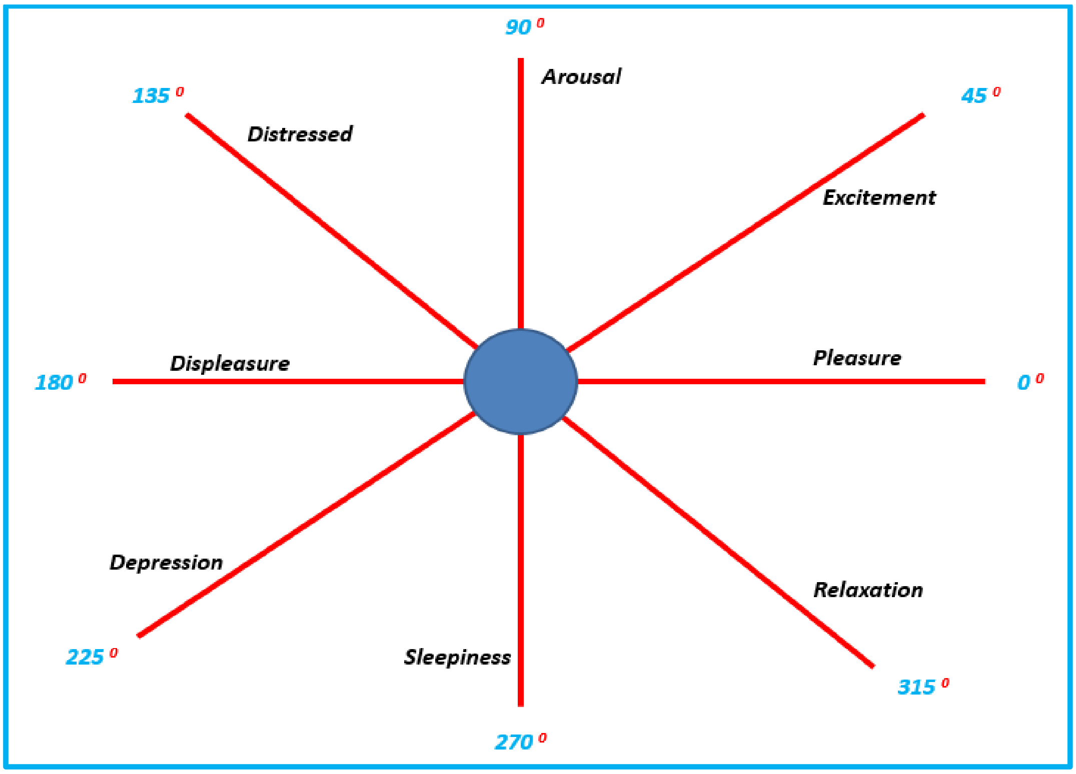



**Figure 2-1 Russell's Circumplex Model of Affect (Russell, 1980)**

Russell's 360° approach is an easy to use model for the representation of emotion(s) on a 2D scale. The Figure 2-2 Emotions on Russell's Circumplex Model extracted from Russell's work demonstrates how 28 emotions may be classified with varying levels of valence and arousal using the Circumplex Model of Affect (Russell, 1980).

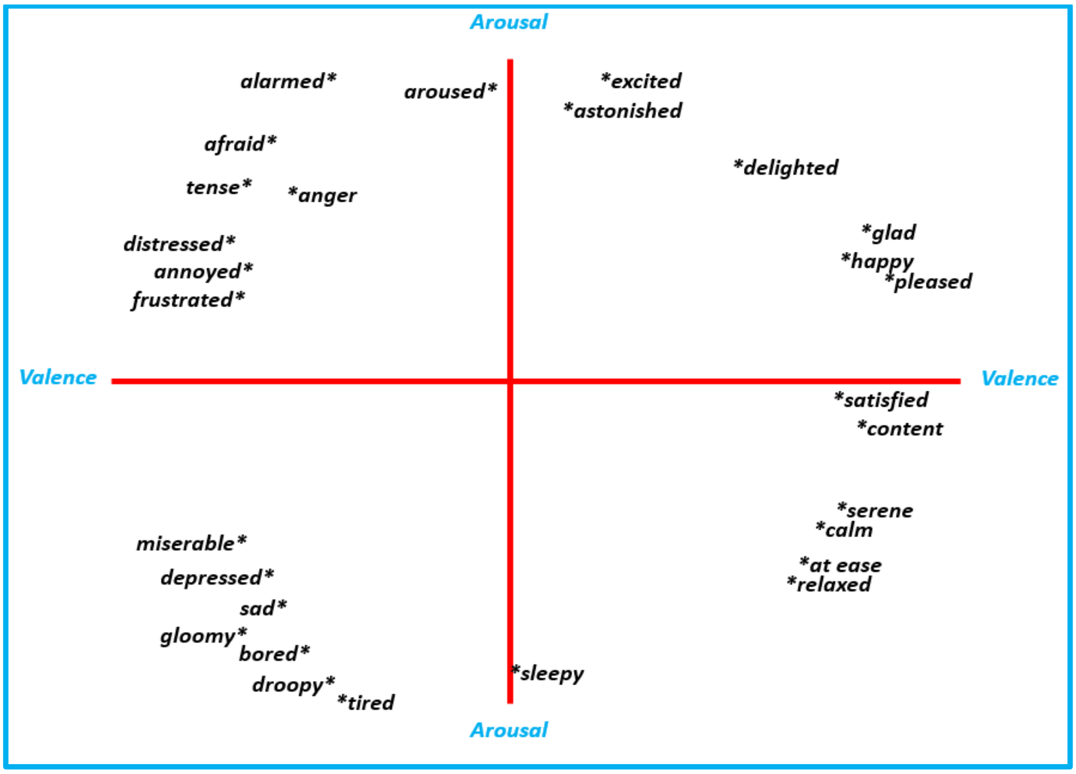



**Figure 2-2 Emotions on Russell's Circumplex Model (Russell, 1980)**

**Energy/Stress Model:** Thayer presents an interesting model in Figure 2-3 Thayer's Energy/Stress Model of Emotions that uses energy and stress for emotion classification (Thayer, 1989) that was described in (Kim , Lee, Kim, & Yoo, 2011) in research relating to music mood classification. The diagram below represents the emotional state of exuberant as high energy and low stress and depression as low energy and high stress.

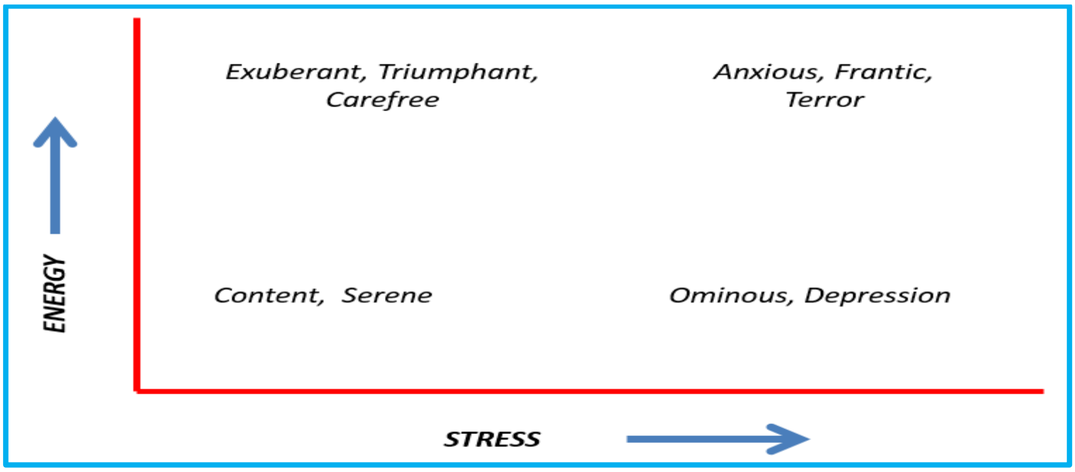



**Figure 2-3 Thayer's Energy/Stress Model of Emotions (Thayer, 1989)**

**OCC Cognitive Model:** The Ortony, Clore and Collins (OCC) Cognitive Model (Ortony, Clore, & Collins, 1990) represented in Figure 2-4 Ortony, Clore and Collins (OCC) Cognitive Emotions Model was originally developed to provide AI systems with emotional reasoning capabilities. The model assumes that emotions arise from valence based reactions to situations consisting of events, agents and objects. The OCC model classifies twenty two emotion types, based on the outcomes of situations which include events, objects and agents. The OCC model highlights the complexity involved in processing and understanding human emotion.

Their research work delves deeper into emotion and cognitive states. It also studies how humans may experience feelings of mixed emotions and how situations may be constructed and viewed from a number of different emotional perspectives. Picard's (1997) Affective Computing refers to the OCC model and states that the *OCC* model is *useful for reasoning about emotions; the cognitive generation of emotions and also can be used to trigger other important emotional consequences* (Picard, 1997), [p. 198].

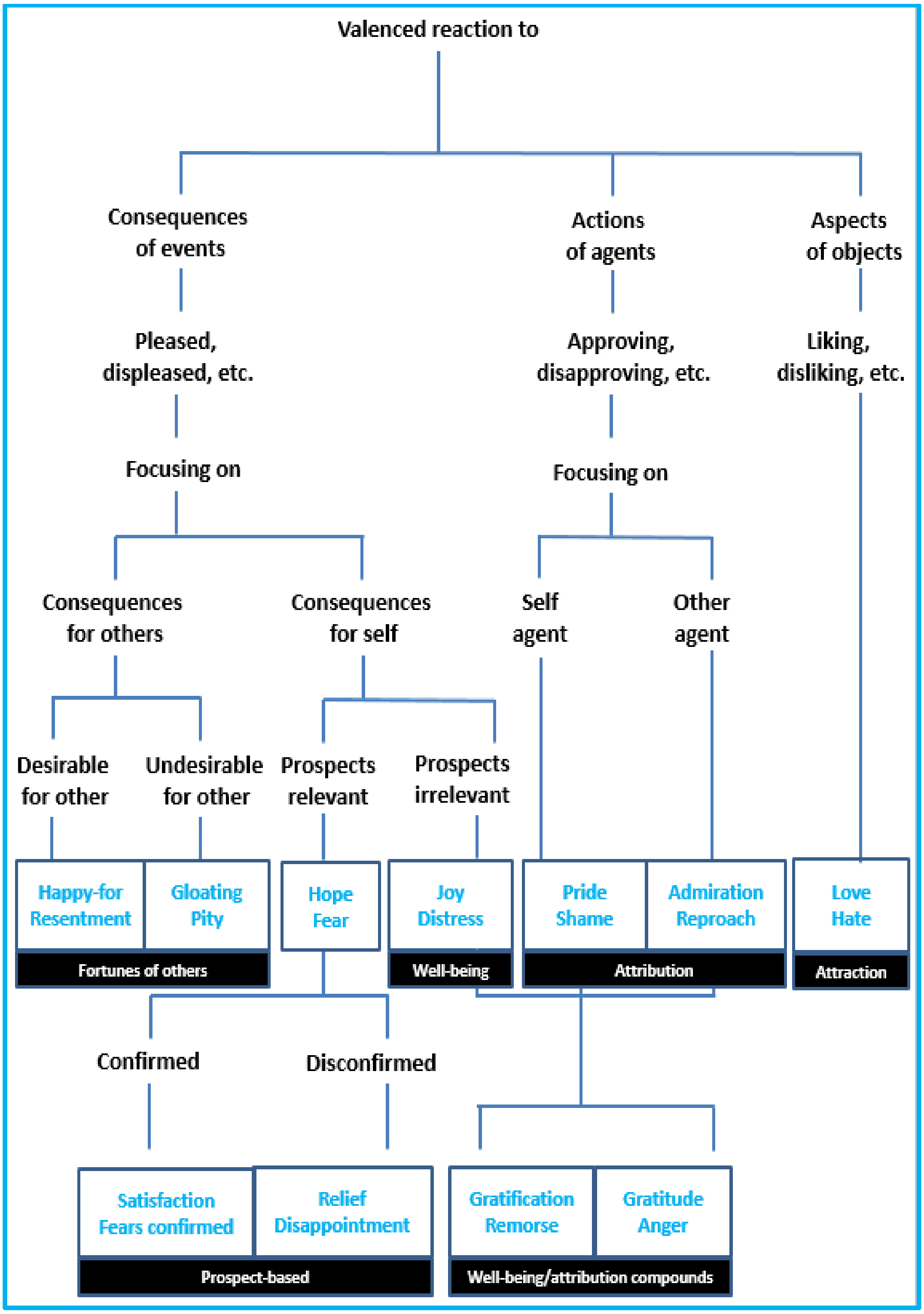



**Figure 2-4 Ortony, Clore and Collins (OCC) Cognitive Emotions Model**

The psychological research and theories distilled into the models discussed above are extremely relevant to the classification of emotions using machine learning and to the development of emotion ontologies (Hastings, Ceusters, Smith, & Mulligan, 2011). These models, with years of theoretical foundation have been extremely influential in assisting the field of AC to advance over the past decade but several issues and challenges still need to be addressed.

For instance, can all emotion be classified into a two dimensional space as referenced in the Russell and Thayer models? Adolphs (Adolphs, 2010) explains a major challenge which not only involves understanding the basic emotions (fear, anger and disgust) but also highlights the need for the understanding of social or moral emotions which have evolved according to Adolphs as a feedback regulatory mechanism for everyday human engagement/interaction with social groups. Such social or moral emotions include *jealousy, pride, shame, guilt and embarrassment* (Adolphs, 2010), [p. 551] and Adolphs also introduces the emotion of Schadenfreude (Jane, 2011) (German) which he claims does not require an equivalent word in English. Schadenfreude is defined as the feeling of joy or delight one may get from the misfortunes of another person and is truly another example of the complex mix associated with emotional theory.

Calvo and D'Mello (Calvo & D'Mello, 2010) also address the social aspects of emotion in their review paper on affect detection. They refer to the work of Averill who proposed that *emotions cannot be explained strictly on the basis of physiological or cognitive terms* (Calvo & D'Mello, 2010), [p. 21], (Averill, 1980). Averill believes that emotions are *primarily social constructs* (Calvo & D'Mello, 2010), [p. 21] and proposes that social analysis must be part of the process of understanding the nature of emotion which links in with the challenges drawn above by Adolphs.

Another significant challenge in the advancement of AC is the limited psychological, cognitive and model interpretation expertise available to computer scientists. Incorrect applications of psychological and cognitive models and theories along with a lack of solid mixed discipline research may lead to over inflated expectations across the AC field due to the lack of a sound AS research basis. Given the complexities and vastness of the AC and AS fields, education institutions may step up to this challenge and provide highly specialised, multi-disciplinary, post-graduate computer science programmes in the future.

### 2.2.3 Psychological Based Tools for Affective Computing Research

The psychological theory, models and frameworks discussed in the previous section have over the years contributed to the development of a range of tools for conducting AC based experiments. For ease of presentation, this sub-section has three headings relating to the generation, determination and recording of emotional responses/states.

**Generating an emotional response/state:** This section presents a number of services developed for the generation of emotional responses.

**Geneva Affective PicturE Database (GAPED):** The Geneva Affective PicturE Database (GAPED) is a database of pictures created to increase the availability of visual emotion stimuli (Dan-Glauser & Scherer, 2011). The database provides for positive, negative and neutral dimensions with pictures rated according to *valence, arousal, and the congruence of the represented scene with internal (moral) and external (legal) norms* (Dan-Glauser & Scherer, 2011), [p. 468]. The GAPED is available for download from the Swiss Centre for Affective Sciences[2].

**LIRIS-ACCEDE Video Database:** The use of current and well validated video that can elicit an emotional response is a vital part of the toolkit for AC researchers. LIRIS-ACCEDE is a video database for affective content analysis

[2] http://www.affective-sciences.org/researchmaterial

(Baveye, Dellandrea, Chamaret, & Chen, 2015) consisting of 9,800 video clips specifically created for affective computing research. All of the video clips have been coded and ranked into the valence-arousal dimension space. The dataset is publicly available to affective computing researchers[3].

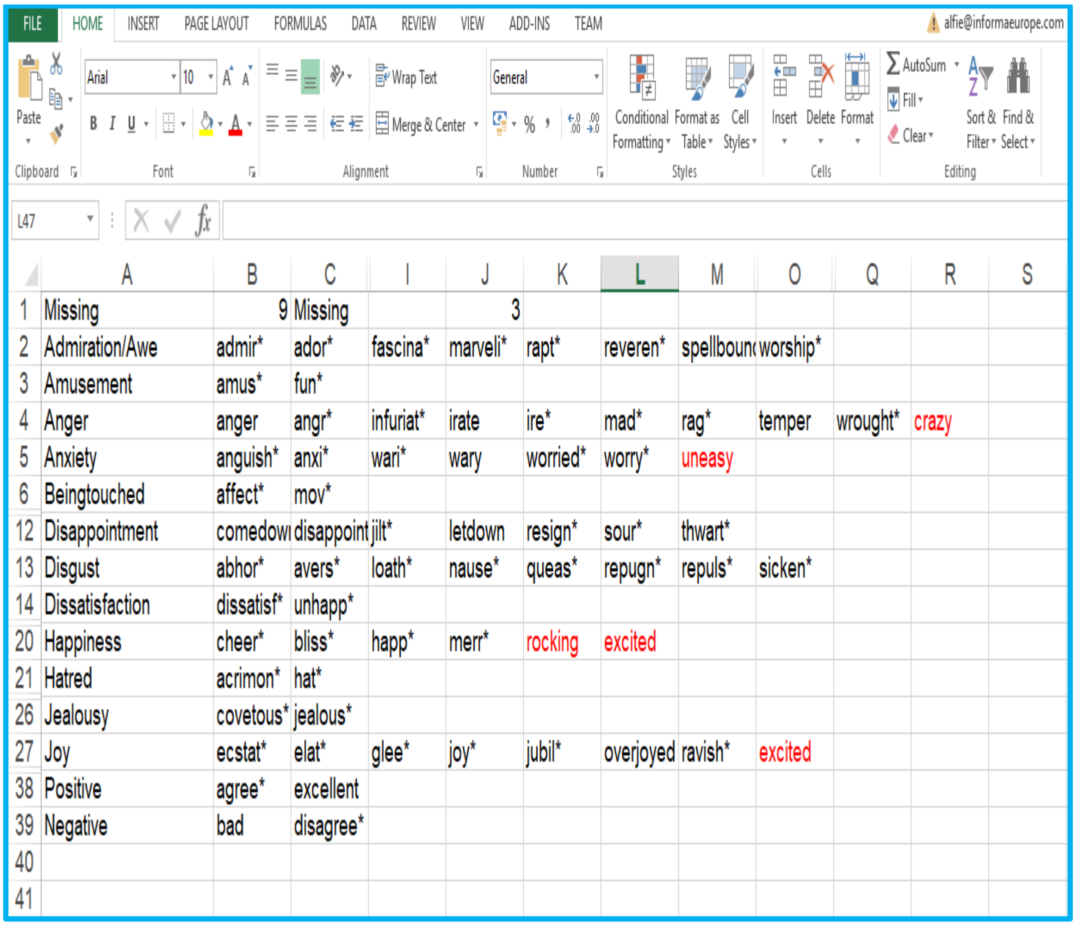
**Man-Machine Interaction (MMI) Facial Expression Database:** The MMI Facial Expression Database provides large volumes of visual data of facial expressions. It has been developed by the Man-Machine Interaction group at Delft University of Technology, Netherlands (Pantic, Valstar, Rademaker, & Maat, 2005). The facial expression database may be used for building, testing and evaluating facial expression recognition algorithms. This will be discussed further in the section on AC vision technologies.

**Determining an emotional response/state:** This section presents the Geneva Affect Label Coder (GALC) as a tool for determining emotions felt.

**Geneva Affect Label Coder (GALC):** Klaus Scherer (2005) has contributed to the development of the Geneva Affect Label Coder (GALC). The GALC facilitates the capture of a free response format for subject self-reporting of emotions felt rather than selecting from a pre-determined set of emotions during an AC experiment. Scherer explains that GALC is an *Excel macro program that attempts to recognize 36+ affective categories commonly distinguished by words in natural languages and parses text data bases for these terms and their synonyms (as based on established thesauri)* (Scherer, 2005), [p. 713]. The GALC addresses the semantics of terminology used in everyday communications to express emotions, moods and other related affective states.

[3] http://liris-accede.ec-lyon.fr/

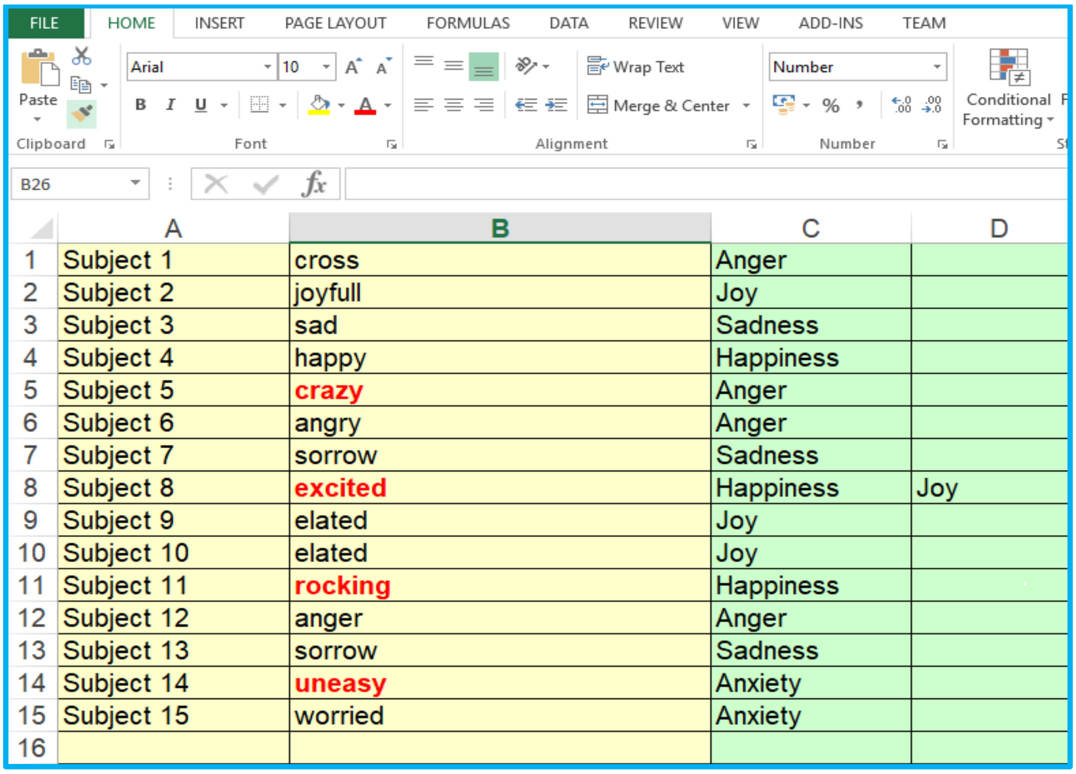
The Figure 2-5 Geneva Affect Label Coder (GALC) – Extract is a reduction of the original GALC for explanation purposes. The column A provides a list of emotion terms used in everyday language. The other columns provide alternative identifiers or synonyms that may be used for the main emotion terms listed in column A. In tests using the GALC, the terms in red were entered in relation to the emotions of Anger, Anxiety, Happiness, and Joy.



| | A | B | C | I | J | K | L | M | O | Q | R | S |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Missing | 9 | Missing | | 3 | | | | | | | |
| 2 | Admiration/Awe | admir* | ador* | fascina* | marveli* | rapt* | reveren* | spellboun | worship* | | | |
| 3 | Amusement | amus* | fun* | | | | | | | | | |
| 4 | Anger | anger | angr* | infuriat* | irate | ire* | mad* | rag* | temper | wrought* | crazy | |
| 5 | Anxiety | anguish* | anxi* | wari* | wary | worried* | worry* | uneasy | | | | |
| 6 | Beingtouched | affect* | mov* | | | | | | | | | |
| 12 | Disappointment | comedowi | disappoint | jilt* | letdown | resign* | sour* | thwart* | | | | |
| 13 | Disgust | abhor* | avers* | loath* | nause* | queas* | repugn* | repuls* | sicken* | | | |
| 14 | Dissatisfaction | dissatisf* | unhapp* | | | | | | | | | |
| 20 | Happiness | cheer* | bliss* | happ* | merr* | rocking | excited | | | | | |
| 21 | Hatred | acrimon* | hat* | | | | | | | | | |
| 26 | Jealousy | covetous* | jealous* | | | | | | | | | |
| 27 | Joy | ecstat* | elat* | glee* | joy* | jubil* | overjoyed | ravish* | excited | | | |
| 38 | Positive | agree* | excellent | | | | | | | | | |
| 39 | Negative | bad | disagree* | | | | | | | | | |
| 40 | | | | | | | | | | | | |
| 41 | | | | | | | | | | | | |

**Figure 2-5 Geneva Affect Label Coder (GALC) – Extract (Scherer, 2005)**

The Figure 2-6 Geneva Affect Label Coder (GALC) - Subject Test Data provides test data from fifteen subjects. The figure demonstrates the use of the free response format and lists the emotional terms entered by subjects for a fictional AC experiment. Notice how the red free response terms of crazy, excited, rocking and uneasy from subjects 5, 8, 11 and 14 respectively were picked up by the GALC and converted into more formal emotion terminology.



| | A | B | C | D |
|---|---|---|---|---|
| 1 | Subject 1 | cross | Anger | |
| 2 | Subject 2 | joyfull | Joy | |
| 3 | Subject 3 | sad | Sadness | |
| 4 | Subject 4 | happy | Happiness | |
| 5 | Subject 5 | **crazy** | Anger | |
| 6 | Subject 6 | angry | Anger | |
| 7 | Subject 7 | sorrow | Sadness | |
| 8 | Subject 8 | **excited** | Happiness | Joy |
| 9 | Subject 9 | elated | Joy | |
| 10 | Subject 10 | elated | Joy | |
| 11 | Subject 11 | **rocking** | Happiness | |
| 12 | Subject 12 | anger | Anger | |
| 13 | Subject 13 | sorrow | Sadness | |
| 14 | Subject 14 | **uneasy** | Anxiety | |
| 15 | Subject 15 | worried | Anxiety | |
| 16 | | | | |

**Figure 2-6 Geneva Affect Label Coder (GALC) - Subject Test Data (Scherer, 2005)**

The model macro program is executed by highlighting the column of free response emotion terms (column B) for each subject and selecting the appropriate language option. The GALC then analyses the free response formats against its internal emotion model as represented in Figure 2-5 Geneva Affect Label Coder (GALC) – Extract . The result is a set of formal emotion terms allocated against each subject one to fifteen.

The GALC is a useful tool for conducting AC research where the research participant needs to be given freedom in terms of their emotional response to a stimulus.

**Recording of an emotional response/state:** This section presents a number of tools used to capture the emotions felt by participants in AC research.

**Geneva Affect Emotion Wheel (GEW):** Klaus Scherer has also contributed to the development of the Geneva Affect Emotion Wheel (GEW). The GEW represented in Figure 2-7 Geneva Affect Emotion Wheel (GEW) has gone through a number of iterations since the original concept presented in Scherer's paper. The current version of the emotion wheel is available as a free download for academic research purposes (Swiss Center for Affective Sciences, 2017). The GEW can be used as a self-reporting tool by subjects for the classification of one or more emotions related to a specific affective experience. The GEW wheel represents two major dimensions of emotion experience with the north representing high control/power and the south representing low control/power. The east and west of the GEW represent positive and negative valence respectively (Swiss Center for Affective Sciences, 2017). The GEW is highly correlated with the theoretical Circumplex Model of Affect (Russell, 1980) previously discussed, with the north-south representing arousal and the east-west representing the valence dimensions.

The GEW differs from the GALC (which relates to the semantic of emotions) and is used for the recording of a pre-determined set of emotions that may be experienced by a subject. Each spike relates to one of twenty different emotions (generally agreed upon by the academic research community) with varying sizes of circles on each spike to reflect the varying levels of emotion intensity experienced by a subject during the event under research.

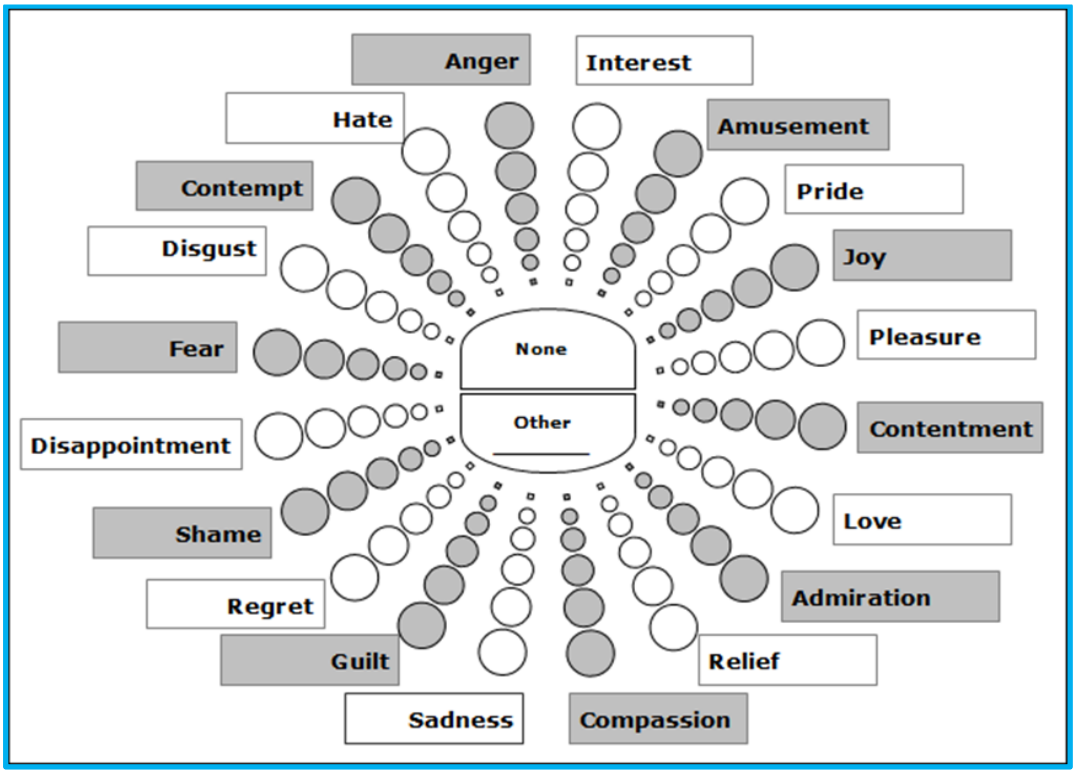



**Figure 2-7 Geneva Affect Emotion Wheel (GEW) (Swiss Center for Affective Sciences, 2017)**

A copy of the GEW Figure 2-7 Geneva Affect Emotion Wheel (GEW) has been reproduced above with the permission of the Swiss Center for Affective Sciences

**Self-Assessment Manikin (SAM):** Another established tool from the AC literature for the capture and recording of an emotional state is the Self-Assessment Manikin (SAM) proposed by Bradley and Lang (Bradley & Lang, 1994) in Figure 2-8 Self-Assessment Manikin (SAM) . SAM uses pictorial images for the non-verbal assessment of measures of pleasure, arousal and dominance in relation to affective reaction to defined stimuli.

In the pictorial representations in the SAM figure, the pleasure dimension (top layer) ranges from smiling to unhappy, arousal (middle layer) ranges from excited to sleepy, and dominance representing control of the situation (bottom layer) from small to large control.

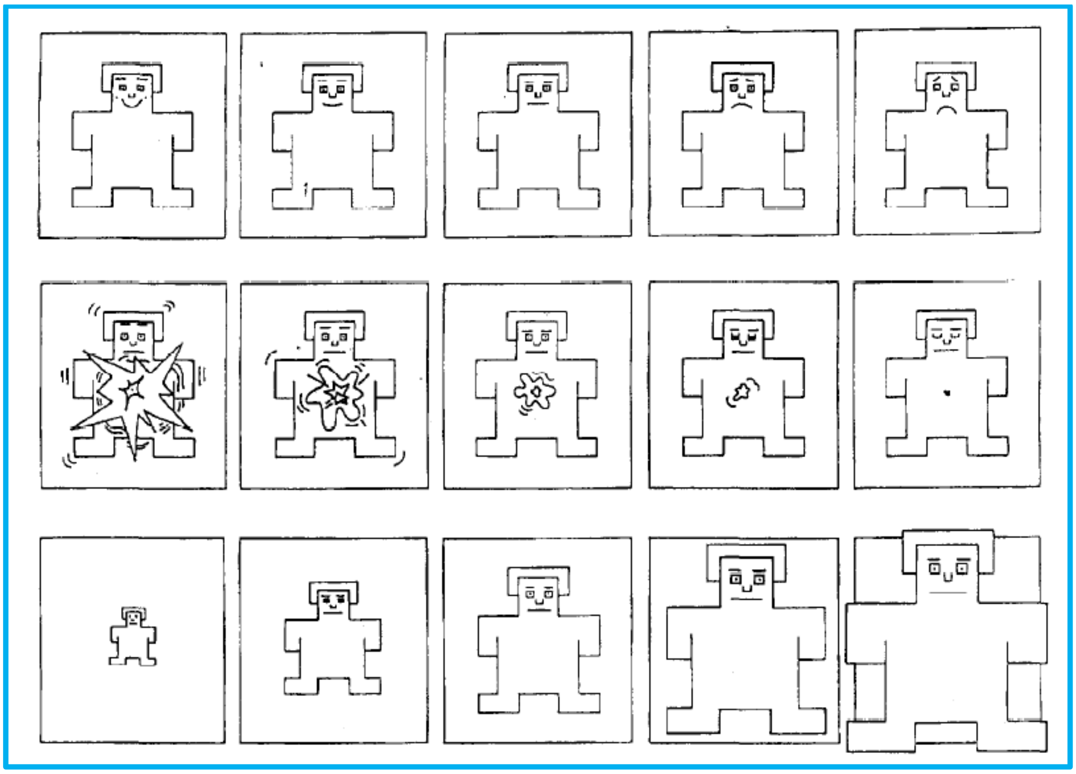
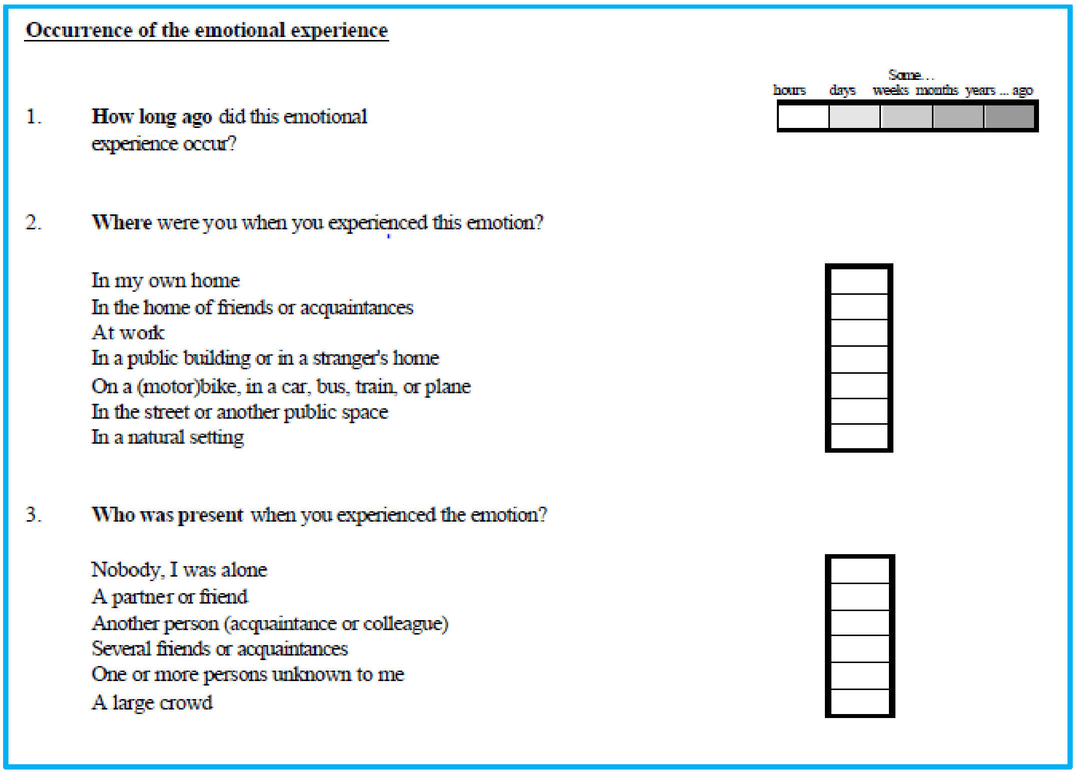


**Figure 2-8 Self-Assessment Manikin (SAM) (Bradley & Lang, 1994)**

**Geneva Appraisal Questionnaire (GAQ):** The Geneva Appraisal Questionnaire (GAQ) (Swiss Center for Affective Sciences, 2017) is carefully crafted to assess an individual's recall and verbal report of a specific emotional episode. The GAQ records a subject's answers to questions relating to novelty, intrinsic pleasantness, goal/need significance, coping potential and compatibility with standards. The GAQ also elicits information on the timing, social context, intensity, duration and regulation of the emotion event/experience under research. Figure 2-9 Geneva Appraisal Questionnaire (GAQ) – Extract provides an example of the opening questions in relation to an emotional experience of a subject.



**Occurrence of the emotional experience**

| | | | | hours | days | Some... weeks | months | years ... ago |
|---|---|---|---|---|---|---|---|---|
| 1. | **How long ago** did this emotional experience occur? | | | | | | | |

2. **Where** were you when you experienced this emotion?

In my own home
In the home of friends or acquaintances
At work
In a public building or in a stranger's home
On a (motor)bike, in a car, bus, train, or plane
In the street or another public space
In a natural setting

3. **Who was present** when you experienced the emotion?

Nobody, I was alone
A partner or friend
Another person (acquaintance or colleague)
Several friends or acquaintances
One or more persons unknown to me
A large crowd

**Figure 2-9 Geneva Appraisal Questionnaire (GAQ) – Extract (Swiss Center for Affective Sciences, 2017)**

The Emotion Analyst (Geneva Emotion Research Group, 2013) is an expert system based web service developed by psychologists that is closely related to the Geneva Appraisal Questionnaire format. The following is a link to the Emotion Analyst platform[4].

### 2.2.4 Using Sensor Technologies for Emotion Detection

So far a number of relevant theories, models, and tools originating from psychology and AS research have been presented in an AC context. So why has AC evolved into a field in its own right? How come the sudden upsurge of interest in AC today? These questions are answered by considering the rapid advances in cloud and platform computing, HPC, machine learning and most certainly

[4] http://www.unige.ch/fapse/emotion/demo/TestAnalyst/GERG/apache/htdocs/start.php?lang=en

developments in the performance and ubiquity of affect detection sensory technologies.

Affect detection sensory technologies possess embedded capabilities to access and process sensory physiological signals from the human body that heretofore were only available to specialised medical and psychological researchers. These evolving sensory devices can be used to compliment and automate the data signal collection process and can also be used in the correlation process of sensory data with user self-report data. This final section discusses the use of sensors across disparate modalities for the attempted recognition of the psychological based phenomenon of emotion (affect).

**Input Sources of Affective Sensory Data:** Below is a brief overview of a number of typical affect detection sensory data sources and related terminology that appear in the psychology, AS and AC literature.

- **Video sources:** Facial expressions, Gestures, Gait, Posture, Oculography (Oxford Dictionaries, 2017)
- **Physiological sources:** Respiration, Galvanic Skin Response (GSR) (Colman, 2015), Temperature, Electrocardiogram (ECG) (Oxford Press, 2015), Heart Rate (HR), Blood pressure, Blood volume pulse, Electromyography (EMG) (Oxford Dictionaries, 2017), Electroencephalogram (EEG) (Oxford Reference, 2017), Magnetic resonance imaging (fMRI) (Oxford Dictionaries, 2017)
- **Auditory:** Voice (Speech), Ambient sound

The main role of the sensory technologies is to deliver affect detection capabilities to AC systems across a range of the above modalities. D'Mello and Kory accurately describe affect detection as a signal processing and pattern recognition problem. They explain how affect detection *involves the development of a classifier or regressor to detect an ill-defined phenomenon (affect) from observable signals* (D'Mello & Kory, 2015), [p. 43:2]. In their research they highlight the trend from single sensor mode (unimodal) to multi-sensor mode (multi-modal) signal processing and provide a meta-analysis of multi-modal affect sensory detection systems.

In relation to multi-modal sensory based AC, Picard discusses systems that can recognise emotions and how they should have intrinsic abilities to infer an emotional state from observations of emotional expressions (visual, physiological, other) and should also possess reasoning capabilities in relation to emotion-generating situations (Picard, 2010).

This primarily information driven model has many scientific advantages in terms of quantification and exactness and will be driven by future IoTs technology developments. The intricacy of inferring and reasoning about and across emotional situations is a highly complex information processing task involving contextual, temporal, environmental, personal and historical reasoning functionality.

Boehner et al. build on the above points and suggest that the *physiological approaches to emotion, in focusing on measuring emotion as objective and well defined, fail to address how emotions are actually experienced* (Boehner, DePaula, Dourish, & Sengers, 2007), [p. 289]. They believe that affect is not only something that is made and measured from body signals but that it is also made from the many complexities of human communications and interactions. Rather than taking the emotion model solely as one that is naturally existing and objectively measurable, (Boehner, DePaula, Dourish, & Sengers, 2007) present emotions as interactionally constructed and subjectively experienced by humans.

While this thesis research is exploring multi-modal affect detection from an information model perspective, the above discussion is evidence of the long road ahead for AC in terms of taking experimentation with multi-modal sensory technologies out of the lab and into emotionally fuelled, interactive, time-variant and subjective real-world scenarios.

## 2.3 Affective Computing Vision: Scientific Aspects and Technologies

There are many relevant sources of AC vision data such as gestures, gait, and posture but facial expression analysis has been one of the major growth areas in AC, particularly in the past number of years. This section primarily focuses on both the scientific and technological aspects of facial expression analysis. The sub-section on the scientific aspects is directly related to AC vision research while the technologies sub-section has a more practical focus in relation to discussion on systems and tools used in AC vision research projects. The chapter section concludes with a summary and discussion of AC vision related remaining problems and challenges.

### 2.3.1 Affective Computing Vision: Scientific Aspects

The objective of this section is to give an introduction to selected scientific research surrounding AC vision techniques. The Facial Action Coding System (FACS) is an observational coding scheme originally developed by Ekman and Friesen in 1978 (Ekman & Friesen, 1978), (Paul Ekman Group, 2015). FACS describes a set of visually distinguishable facial activities using coded facial expressions known as Action Units (AUs) and categorises head and eye position movements. FACS also provides for the coding of the intensity of each facial action. Figure 2-10 Facial Action Coding System (FACS) Extract provides the AU number, associated description and the related muscular basis.

TABLE 1.1. Single action units (AU) in the Facial Action Coding System

| AU number | Descriptor | Muscular Basis |
|---|---|---|
| 1. | Inner Brow Raiser | Frontalis, Pars Medialis |
| 2. | Outer Brow Raiser | Frontalis, Pars Lateralis |
| 4. | Brow Lowerer | Depressor Glabellae, Depressor Supercilli; Corrugator |
| 5. | Upper Lid Raiser | Levator Palpebrae Superioris |
| 6. | Cheek Raiser | Orbicularis Oculi, Pars Orbitalis |
| 7. | Lid Tightener | Orbicularis Oculi, Pars Palebralis |
| 9. | Nose Wrinkler | Levator Labii Superioris, Alaeque Nasi |
| 10. | Upper Lip Raiser | Levator Labii Superioris, Caput Infraorbitalis |
| 11. | Nasolabial Fold Deepener | Zygomatic Minor |
| 12. | Lip Corner Puller | Zygomatic Major |
| 13. | Cheek Puffer | Caninus |
| 14. | Dimpler | Buccinator |
| 15. | Lip Corner Depressor | Triangularis |
| 16. | Lower Lip Depressor | Depressor Labii |
| 17. | Chin Raiser | Mentalis |
| 18. | Lip Puckerer | Incisivii Labii Superioris; Incisivii Labii Inferioris |
| 20. | Lip Stretcher | Risorius |
| 22. | Lip Funneler | Orbicularis Oris |
| 23. | Lip Tightener | Orbicularis Oris |
| 24. | Lip Pressor | Orbicularis Oris |
| 25. | Lips Part | Depressor Labii, or Relaxation of Mentalis or Orbicularis Oris |
| 26. | Jaw Drop | Masetter; Temporal and Internal Pterygoid Relaxed |
| 27. | Mouth Stretch | Pterygoids; Digastric |
| 28. | Lip Suck | Orbicularis Oris |

**Figure 2-10 Facial Action Coding System (FACS) Extract (Ekman & Friesen, 1978)**

Rosenberg (2005) produced a Study of Spontaneous Facial Expressions in Psychology (Rosenberg, 2005). This work discussed how experts at the time in computer science and psychology were researching artificial neural network (ANN) (Schalkoff, 1997) algorithms to automate facial measurement. Rosenberg argues that within the next decade, procedures would become available which would lead to a proliferation of research on spontaneous facial expression.

One of the systems to emerge at this time was the Automated Facial Expression Recognition System (AFERS) (Ryan, et al., 2009) based on FACS. This was developed by the Robotics Institute of Carnegie Mellon University and is an example of FACS application for emotion recognition. AFERS processes each video frame to produce facial shape and appearance features which are then input to a *support vector machine* (SVM) (OpenCV, 2017) *for expression recognition* (Ryan, et al., 2009) , [p. 176]. An example of AFERS emotion facial recognition processing is represented in Figure 2-11 AFERS - Seven Universal Emotion Expressions .


**Figure 2-11 AFERS - Seven Universal Emotion Expressions (Ryan, et al., 2009)**

AFERS addressed two of the major drawbacks of FACS which was the need to have trained FACS coders interpret the video images and the lack of real-time processing capabilities. AFERS is an example of one of the main developmental steps towards Rosenberg's earlier prediction.

Calvo and D'Mello (2010) conducted a review of affect detection techniques (Calvo & D'Mello, 2010). They point to a shortcoming of FACS relating to the fact that it was originally developed for facial expression recognition from still images rather than from imagery changing over time. In human interactions, facial muscles rapidly change and this temporal transition knowledge may be lacking in still imagery. This limitation has not constrained the use of FACS as a fundamental theoretical foundation and it is still the basis for a number of academic and commercial platforms that process images and videos for vision based emotion analytics.

Happy and Routray (2015) discuss how most of the existing algorithms such as FACS rely upon facial geometry that tracks the shape, size and facial components of the human face. This type of recognition requires highly accurate visual data in near perfect conditions and has major limitations when taken out of the lab into real-world practical situations. To address these limitations, Happy and Routray propose a *novel facial landmark detection technique as well as a salient (striking) patch based facial expression recognition framework with significant performance at different image resolutions* (Happy & Routray, 2015), [p. 2]. In their research, they discuss a framework for automated facial landmark detection and the extraction of active facial patches that are most striking in an image. The salient facial patches are actual locations in the facial image frame data as represented in the Figure 2-12 Position of Facial Patches which shows salient facial patches P1 to P19.

Happy and Routray (2015) explain that in the literature, *facial features are concatenated to recognize the (facial) expression* and that it generates feature vectors of high dimensionality while *features from a fewer facial patches can* *replace the high dimensional features without significant diminution of the recognition accuracy* (Happy & Routray, 2015), [p. 6].

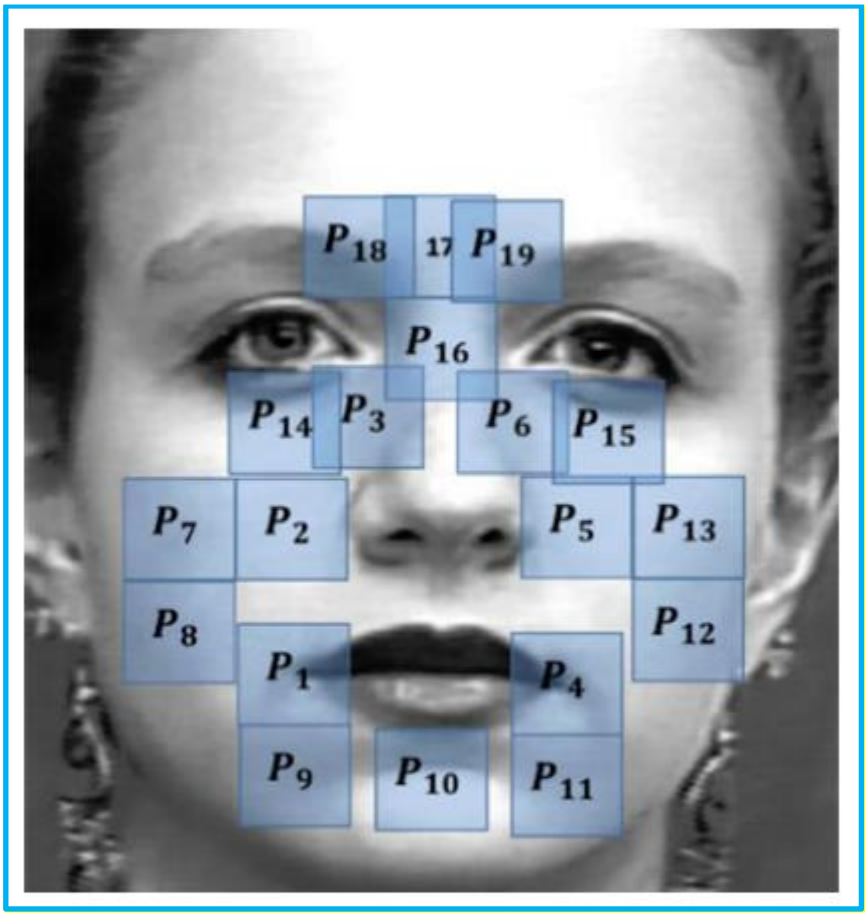



**Figure 2-12 Position of Facial Patches (Happy & Routray, 2015)**

Appearance features (extracted from the salient facial patches) are input to a multi-class classifier that classifies images into six basic emotion expressions (anger, fear, disgust, happiness, sadness, surprise). Happy and Routray (2015) tested their system using two image databases, Cohn-Kanade (CK+) (Lucey, et al., 2010) and JAFFE (Lyons, 2010). They reported that their *system appears to perform well in CK+ data set with an F-score (Brownlee, 2018) of 94.39 percent. Using the salient patches obtained by training on CK+ data set, the system achieves an F-score of 92.22 percent in JAFFE data set* (Happy & Routray, 2015), [p. 10]. Significantly, the research system was also tested in conditions of varying resolution quality which is an obvious and challenging limitation of current vision based AC interfaces.

Attentiveness, concentration, absorption, focus, awareness, application, and engagement are all explanatory words that are used in relation to varying levels of interaction performed by humans, in everyday activities. The observation of these levels of human interaction and the possible intervention by AC powered systems, opens up multiple application potentials in many of the domains already discussed.

Whitehill et al. (Whitehill, Serpell, Lin, Foster, & Movellan, 2014) conducted research in human interaction and more specifically into student engagement. Their work explains how human observers go about the process of engagement evaluation from facial expressions. Their research concentrates on automatic facial recognition using video as the most applicable non-invasive method where students are concerned and it is also relevant to learning and system interfaces.

They used machine learning techniques to develop automatic engagement detectors for the binary classification of high versus low engagement. An initial detector performed face registration which involved cropping the face from an image to a 48 x 48 pixel patch. Four categories of engagement were then classified (1 = lowest, 4 = highest) using four individual binary classifiers. Whitehill et al. (2014) compared *three commonly used and demonstrably effective feature type + classifier combinations from the automatic facial expression recognition literature* (Whitehill, Serpell, Lin, Foster, & Movellan, 2014), [p. 91]. The three expression recognition techniques used were GentleBoost (Friedman, Hastie, & Tibshirani, 2000) with Box Filter features (Viola & Jones, 2004) (Boost (BF)); SVMs with Gabor features (SVM (Gabor)) and

Multinomial logistic regression with expression outputs from their Computer Expression Recognition Toolbox (MLR (CERT)) (Littlewort, et al., 2008).

The outputs of the four binary classifiers were then *fed to a regressor to estimate the image's engagement level* (Whitehill, Serpell, Lin, Foster, & Movellan, 2014), [p. 91]. Two alternative regression strategies were used in this stage of the research, *(1) linear regression for real-valued engagement regression, and (2) multinomial logistic regression for four-way discrete engagement level classification* (Whitehill, Serpell, Lin, Foster, & Movellan, 2014), [p. 94].

Their research concluded that for the binary classification of high/low engagement, the automatic detection system performed as well as the human observers used in their research experiments which had Cohen's k = 0.96. It was also found that the classification accuracy was very similar for all of the three machine classifiers tested, MLR (CERT) = 0.714, Boost (BF) = 0.728, and SVM (Gabor) = 0.729 and closely matched the classification performed by human coders on levels of engagement which had accuracy = 0.696 (Whitehill, Serpell, Lin, Foster, & Movellan, 2014), [p. 93].

One notable observation highlighted was that the MLR (CERT) classifier (which is based on FACS, see (Whitehill, Serpell, Lin, Foster, & Movellan, 2014) [p. 6], may have some inaccuracies in relation to eye closure. This issue was identified as many images that contained eye closure were being labelled as the lowest level of engagement (Engagement = 1). Boost (BF) and SVM (Gabor) seemed to have outperformed MLR (CERT) with better accuracy rates when the subject's eyes were closed.

In the advertising sector, 'zapping' refers to a viewer that stops watching a commercial (lack of engagement). The Zapping Index is a proposal by Yang et al. (Yang, Kafai, An, & Bhanu, 2014) as a measure of the zapping potential on advertisements, and is designed to make the viewer more engaged, interested and happy. Their work describes the use of machine learning techniques for two binary classifiers of smile detection and zapping behaviour.

Faces are extracted from an image using the Viola-Jones face detection algorithm (Viola & Jones, 2004) using a smiling and neutral face as the two output classification labels. A SVM was used and the classifier was trained on multiple data sets made up of 1,543 smiling faces and 2,035 neutral faces, see reference (Yang, Kafai, An, & Bhanu, 2014), [p. 434].

For the zapping classifier, features such as zapping distribution (portion of advertisement watched), mean smile response, maximum smile response and the volume of smile responses were used in a second SVM for the zapping and non-zapping behaviour classifier. Yang. et al. qualify their research with reference to the work of McDuff et al. (McDuff, Kaliouby, Senechal, Demirdjian, & Picard, 2014) which showed how automatic measurement of advertisement preferences could be performed using the smile response. The authors claim that their Zapping Index (ZI) which is derived using the smile emotional response is a newly defined *type of user information which directly shows viewer's preference* (Yang, Kafai, An, & Bhanu, 2014), [p. 442]. Specific results from zapping classification research indicate that *if a sequence's maximum smile response is above 0.5, then the chance is higher that it belongs to the non-zapping class, and vice versa for maximum smile response below 0.5* (Yang, Kafai, An, & Bhanu, 2014), [p. 436]. For an image sequence, the probability value reaches the highest for the non-zapping class if the maximum smile response is above 0.9 while the probability for the zapping class is at its highest when the maximum smile response is less than 0.1.

This research is quite significant as it demonstrates how AC techniques can be used to create new knowledge and in this case a new form of user response measure (ZI) for the advertising sector. Engagement recognition has multi-domain applications (learning, user/work interfaces, business, insurance, eHealth, etc.) and has implications for human machine interfaces and citizen health and safety standards.

The next section switches from the above scientific perspective and presents a selection of open source and commercially available vision related AC sensor technologies.

### 2.3.2 Affective Computing Vision: Technologies

This section presents an overview of selected tools and technologies that are available to the research community working with AC vision. Open Source Computer Vision Library (OpenCV) (OpenCV, 2018) is a computer vision and machine learning library and is a valuable starting point. The software library has over 2,500 C++ based algorithms and those relevant to AC include detection and face recognition; classification of human actions in video images and eye movement tracking.

The OpenCV community is also an active source of algorithm innovations and vision data sets for machine learning. Divisions of Google, Microsoft, Intel and IBM are actively involved in using OpenCV in their vision based research and platform products. Recent acquisition of Itseez (OpenCV, 2016) by Intel headlines their advance into IoTs segments, automotive and vision applications *where the ability to electronically perceive and understand images paves the way* *for innovation and opportunity* (OpenCV, 2016). Davis from the Internet of Things (IoT) group at Intel discusses how vision technologies will drive the emerging *autonomous era* of the IoTs *when devices will require constant connectivity and will need the intelligence [vision analytics] to make real-time decisions based on their surroundings* (Intel, 2016).

Related to OpenCV is OpenVX (Khronos Group, 2016) which is a standard for cross platform acceleration of computer vision applications. This was developed by the Khronos group, which in addition to vision standards also developed cross platform standards for graphics, parallel computing and dynamic media. OpenVX provides performance and power-optimisation processing for embedded and real-time vision applications (Khronos Group, 2016).

The AC group at MIT provide access to selected software tools and resources. Their vision based Attention Meter (Chia-Hsun, Wetzel, & Selker, 2006) is able to track facial attention from multiple faces in real-time. The software was developed by using OpenCV algorithms for face location and movement. Mood Meter (Hernandez, Hoque, Drevo, & Picard, 2012) is another MIT AC vision platform that can assess and display smile intensities and thus relay the overall mood/sentiment of a group scene. Mood Meter was used at MIT in a crowd-source capacity to track the overall mood metrics across the campus during various intervals. Quantitative analysis reported *periodic patterns (e.g., more smiles during the weekends) and strong correlation with campus events (e.g., fewer smiles during exams, most smiles the day after graduation), reflecting the emotional responses of a large community* (Hernandez, Hoque, Drevo, & Picard, 2012), [p. 301].

One vital finding from this large scale in-the-wild AC project was that privacy was one of the main concerns and acted as a core design constraint. Significantly, Mood Meter did not record any live video and it constantly reminded users interacting with the platform of this fact. MIT found that this transparent approach was the best strategy to gain participants' acceptance and to influence interaction and usage.

As introduced in the previous psychology section, the Man-Machine Interaction Group at Delft University of Technology initiated the MMI facial expression database project[5]. In 2005, Pantic et al. (Pantic, Valstar, Rademaker, & Maat, 2005) found a severe lack of well-founded databases for the facial analysis research community. See Table 1 in (Pantic, Valstar, Rademaker, & Maat, 2005), [p. 1] for an overview of facial recognition databases reviewed at that time. Today the MMI database contains recordings of the full temporal pattern of facial expressions, six basic emotion representations and other forms of naturalistic expression. Recent statistics from the MMI site (Delft University, Netherlands, 2017) listed 2,894 sessions in the database with 1,395 sessions with AU coding and 197 sessions labelled as one of six basic emotions.

One of the database projects reviewed by Pantic et al. was developed by the University of Stirling and University of Aberystwyth, the Stirling/ESRC 3D Face Database[6]. The database contains images from many perspectives, including varying focal lengths, indoors, outdoors, varying camera angles, walking and seated video and images as time changes. For emotion recognition, a 3D camera system was used to capture images with *neutral, smile mouth closed, smile*

[5] http://mmifacedb.eu/
[6] http://pics.psych.stir.ac.uk/ESRC/index.htm

*mouth open, anger, disgust, fear, sad and surprised expressions* (University of Stirling and University of Aberystwyth, 2017). Sample images from the database are represented below in Figure 2-13 Stirling/ESRC 3D Face Database.

**Figure 2-13 Stirling/ESRC 3D Face Database (University of Stirling and University of Aberystwyth, 2017)**

A second project referenced by Pantic et al. (2005) is the Japanese Female Facial Expression (JAFFE) database[7] which has expressions posed by ten Japanese female models with each image rated on six emotion adjectives by sixty Japanese subjects (Lyons, 2010), (Lyons, Akemastu, Kamachi, & Gyoba, 1998). JAFFE was used in facial expression research on cultural nuances which found evidence that interaction with others in a *particular cultural context* involves a form of learning that recognises *culture-specific* facial expressions (Dailey, et al., 2010), [p. 1].

Two other relevant datasets are referenced by Samara et al. (2017) in their paper, Affective state detection via facial expression analysis within a human–computer interaction context (Samara, Galway, Bond, & Wang, 2017). Lucey et al. published a dataset known as the Extended Cohn-Kanade (CK-Plus) that contained 593 sequences taken from 123 subjects and included the states of angry, contempt, disgust, fear, happy, sadness and surprise (Lucey, et al., 2010). Lundqvist et al. (1998) produced the Karolinska Directed Emotional Faces dataset (KDEF). KDEF consists of 4,900 pictures from 70 subjects that acted out

[7] http://www.kasrl.org/jaffe.html

seven affective states of afraid, angry, disgusted, happy, neutral, sad and surprised (Lundqvist, Flykt, & Ohman, 1998).

Chehra is a *fully-automatic real-time face and eyes landmark detection and tracking software capable of handling faces under uncontrolled natural setting* (Asthana & Zafeiriou, 2017). The software was developed by Akshay Asthana and Stefanos Zafeiriou at Imperial College London and is available for academic and non-commercial use. The authors claim that Chehra has the following features: automatic system capable of tracking face and eyes at over 80fps, tracks 49 facial landmark points, and tracks 10 eye landmark points (Asthana & Zafeiriou, 2017), (Asthana A. , Zafeiriou, Cheng, & Pantic, 2014).

So far the discussion has presented academic, open-source, recognised standards and freely available technologies for AC vision based research. The increased capabilities of vision systems have certainly been advanced by academic research and the availability of standard libraries and datasets over the past decades. This has led to global players such as Intel, Google, Microsoft (all with dedicated research groups) and others working on various types of vision based platforms, solutions and services. These developments have also complemented parallel research and developments in AC. The next discussion presents a review of a selection of commercially available vision processing technologies that have emerged over the past number of years and discusses some of their key features and relevance to the field of AC.

Intel has heavily invested and today it has major interests in vision related research (Bohn, 2016). The launch in 2013 of Real Sense (formerly known as Intel Perceptual Computing) was an indication of how they prospected on the emergence and importance of computer vision and 3D to maintain and advance their core market position. Today the Real Sense SDK platform provides software engineers with capabilities to integrate sensing technologies for computer vision involving people, objects and robots (Intel, 2017). For example the Real Sense SDK algorithms include hand and cursor movement; speech recognition; user segmentation and many more algorithms for 3D manipulation and vision.

The Real Sense face tracking and recognition module (Intel, 2017) is of most relevance to vision and AC. This module provides the following algorithms:

- Face detection from an image or video.
- Landmark data of 0 to 77 facial points including specific detection of eyes, mouth, etc.
- Pose detection estimates to identify where the user is looking.
- Expression detection that picks up eye closure and smiles etc.
- Face recognition from a stored images database.
- Pulse recognition from changes in facial skin colour.
- Gaze tracking for estimates of eye location on a screen.

The research community is also exploring and embracing the many features of the Real Sense platform. Yang et al. (2016) investigated the use of the Real Sense depth Camera R200 in developing an assistance system for the visually impaired. Their system incorporated a wearable prototype and an audio interface and was found to be *useful and reliable by a field test with eight visually impaired volunteers* (Yang, Wang, Hu, & Bai, 2016) [p. 1]. Draelos et al. (Draelos, Qiu, Bronstein, & Sapiro, 2015) conducted investigation and development with the Real Sense SDK to evaluate its effectiveness for gaze tracking in human computer interaction and mental health diagnosis applications.

Patil and Bailke (Patil & Bailke, 2016) used Real Sense depth based landmark data from frame images captured on the SR300 camera. The geometric distance between landmarks was used for the extraction of features. A Multilayer Perceptron (MLP) neural network algorithm using the backpropagation method was used for image classification. The researchers claim that their *proposed system recognizes three facial expressions namely neutral, happy, and surprised* with a recognition accuracy rate of 93.33% (Patil & Bailke, 2016), [p. 1].

SIGMA researchers, Healy, Keary and Walsh (Healy, Keary, & Walsh, 2016) presented a Real Sense based prototype proof of concept for a mobile agitation tracking (MAT) system for use in elderly and dementia care use cases at CERC 2016 (CERC, 2017). The MAT project aims to develop and evaluate an initial set of algorithms that can detect agitation, restlessness and aggression in dementia patients. MAT uses Real Sense SDK depth data components for vision based analytics to track a subject's facial expressions in real-time. The early versions of MAT have implemented use cases for the detection of restlessness and aggression. The project prototypes also have the potential to be used in more advanced machine learning and data analytics applications typically for research purposes on elder care. Data sets produced by MAT are generated in CSV file format for onwards cloud and database processing or as inputs to machine learning classification algorithms/platforms. For further details and features review of Real Sense and other vision depth sensors such as Kinect and Leap Motion see (Vokorokos, Mihaľov, & Leščišin, 2016).

One of the issues with Real Sense over the years has been the many changes to the platform and its dependence on third party solutions integration. A situation arose in 2016 when Apple acquired Emotient a leader in AC vision recognition

(Winkler, Wakabayashi, & Dwoskin, 2016). Prior to the Apple acquisition a sub-set of the FACS based Emotient algorithms were part of Real Sense under the emotion recognition module. This module has since been removed from recent editions of the SDK.

The research conducted for this thesis has involved using various versions of the Real Sense SDKs (including the original Perceptual Computing platform) in the development of prototypical software artifacts. This will be discussed further in the remaining chapters of the thesis.

The Microsoft Face Tracking SDK (Microsoft, 2015) for Kinect Windows SDK offers 3D tracking results using the Kinect coordinate system. The SDK provides developers with eighty seven 2D and thirteen 3D facial tracking points and processes head pose angles to provide data on yaw, pitch and roll. While the face tracking SDK does not offer direct affective computing algorithms, the literature has references relating to the use of the Kinect for emotion recognition.

Research by (Qi-rong, Xin-yu, Yong-zhao, & Xiang-jun, 2015), introduces the use of the Kinect for emotion recognition and the development of an algorithm that uses both 2D and 3D facial expression features. An overview of the architecture under development for this research is provided in Figure 2-14 Kinect 2D and 3D Emotion Recognition Architecture.

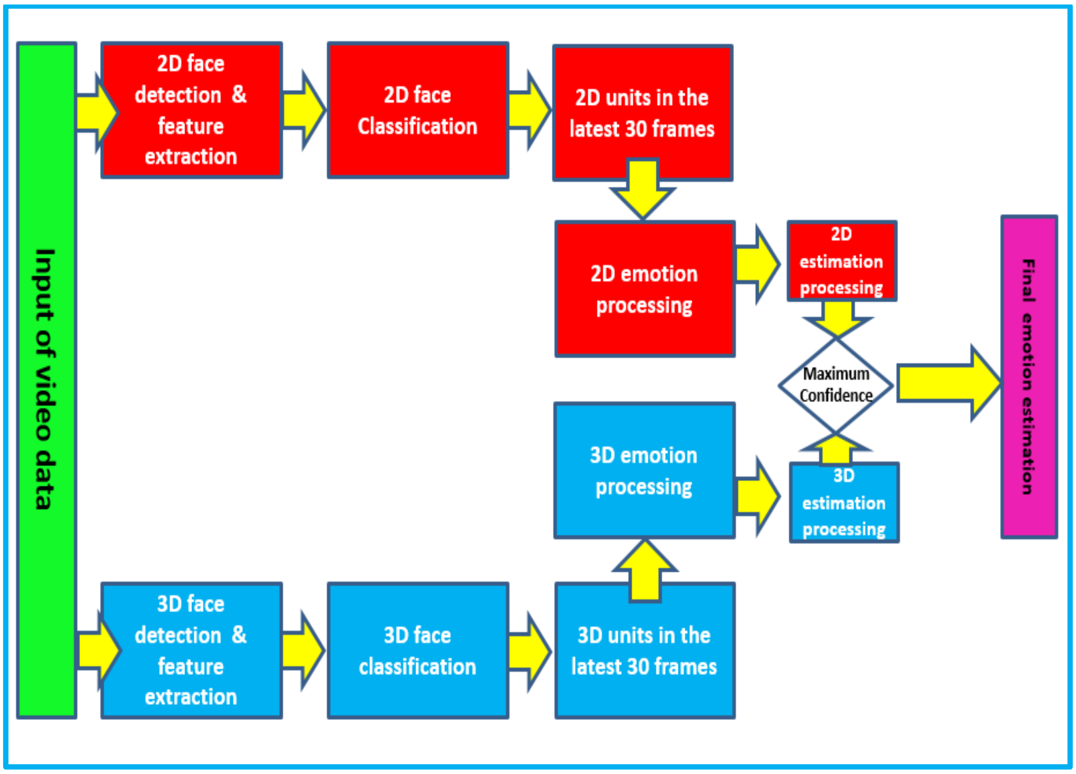



**Figure 2-14 Kinect 2D and 3D Emotion Recognition Architecture**

Microsoft Cognitive Services (MCS) (formerly Project Oxford) have been launched to provide developers with access to *emotion and video detection; facial, speech and vision recognition; and speech and language understanding* (Microsoft, 2017). Of relevance to this review is the MCS Vision API (Microsoft, 2017) for image and object recognition and the Face API (Microsoft, 2017) which performs face detection with associated attributes and facial recognition. MCS also provides a dedicated Emotion API (Microsoft, 2017) which according to Microsoft is capable of detecting the emotional states of *happiness, sadness, surprise, anger, fear, contempt, disgust or neutral* (Microsoft, 2017).

The MCS emotion API for images can process face sizes from 36 x 36 to 4,096 x 4,096 pixels and up to a maximum of 64 faces. Frontal and near-frontal images give best results with problems arising with certain head poses and occlusion. The emotion API for video, handles face sizes between 24 x 24 to 2,048 x 2,048 pixels and can also process a maximum of 64 faces per video. Video file size is limited to 100MB with common video formats supported. MCS also advise that the contempt and disgust emotions are currently at an experimental stage.

While Intel are strongly focused on the developer community in bringing vision based software innovations to market, the current exclusion of dedicated emotion algorithms is a serious set-back to the AC research community but one that may be addressed in the future iterations of the Real Sense SDK platform. Microsoft on the other hand offer dedicated vision and emotion APIs via the cloud/Azure based MCS platform.

IBM's Watson (IBM, 2017) acts as the powerhouse to their Visual Recognition service. This service has similar functionality to the MCS API. Images can be analysed to identify scenes, objects, faces, and other content. The system relies on the deep learning algorithms and capabilities of Watson and is general purpose with many use cases for insurance, retail, manufacturing, education and many more. The API also provides capabilities for building customised vision classifiers. The following video link located at[8] (IBM, 2016) demonstrates the construction and training of a basic superhero classifier using the IBM Visual Recognition platform.

According to an IBM blog post, emotion classification is not a feature of the visual recognition platform but could be addressed via the custom classifier functionality (Gong, 2016) of the service. This has potential and could be useful for future research and development of a customised Watson based AC adaptor across a range of the future application domains already discussed. IBM *view emotion*

[8] https://www.youtube.com/watch?v=U-yJYHks1_s

*detection as a central piece of the puzzle to make AI systems compassionate* (Gundecha, 2016).

Google Cloud Vision (GCV) API provides services for developers that wish to understand and process the content of images. GCV includes image classification, detection of objects and faces, finding and printing recognised words contained in images and moderation of offensive content (Google, 2017). Purely from a vision analytics perspective, GCV can detect and label categories of things from an image; identify popular logos; label well known landmarks; identify text, relevant language and extract text from an image. The face detection module can identify multiple faces in an image and has fundamental emotional processing capabilities.

The sample image in Figure 2-15 Google Cloud Vision - Multi-face Recognition demonstrates the likelihood of joy, sorrow, anger and surprise in an image and demonstrates multi-face processing. GCV has limited AC functionality but the services can be developed further as part of customised applications.

The lack of dedicated AC capabilities, no formal SDK for GCV, evolving complexities of the pricing models and the permanency of the platform may act as a likely hindrance to its long-term uptake by the AC research community. That said, GCV certainly offers a very direct and effective service for developers to quickly AC enable their applications using ubiquitous vision sensors.

Amazon AI (Amazon, 2017) (AAI) provides machine learning and deep learning technologies in the form of Amazon Lex which provides tools for conversational interfaces via voice and text.

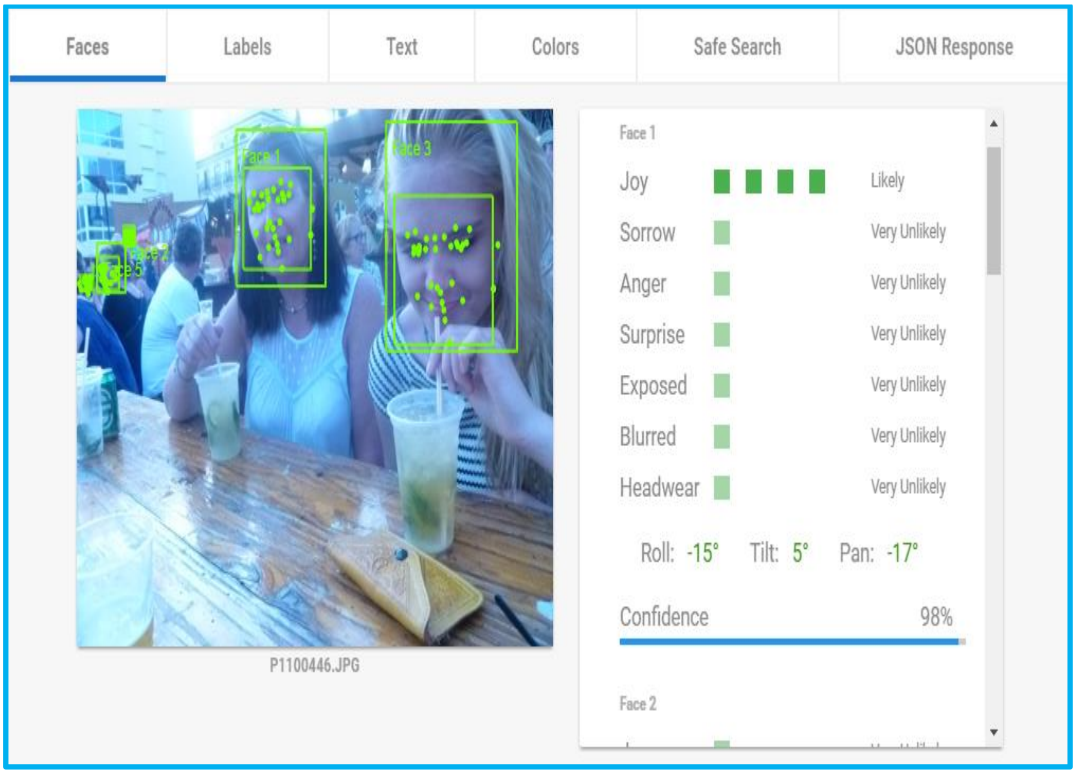



**Figure 2-15 Google Cloud Vision - Multi-face Recognition (Google, 2017)**

AAI service Rekognition (Amazon, 2017) is comparable to other service providers and performs object and scene detection with confidence scores, facial image processing that offers face comparison for similarity across two different images and facial recognition to find similar faces in a large collection of images. Rekognition's facial analysis can detect up to 15 faces in an image (Amazon, 2017) and picks out attributes such as smiling, eyes open/closed, and male/female classification which may be used for sentiment analysis.

Rekognition is currently focused on images only and video processing capabilities are not provided. While emotion analytics are provided for sentiment analysis, the breadth and depth for AC purposes is not a focus for Amazon. Rekognition is comparable to MCS and GCV, their pricing model is clear and well-presented and for those already on the Amazon cloud services they could easily AC enable their systems particularly from a sentiment analysis perspective.

Affectiva (Affectiva, 2017) spun out of MIT and started out in wearables and quickly re-focused on AC vision. Their Affdex platform provides facial detection capabilities for analysing muscular micro-shifts to identify a smile versus a smirk, a yawn and even moments of confusion (Affectiva, 2017). Using real-time facial visual analytics, Affdex can also identify subject states such as surprise, concentration, smiling, disliking, valence, attention and expressiveness. The Affdex system is primarily used to measure the emotional and attention responses from subjects looking at video content (advertising and media industries).

Affectiva have opened their platform to developers and provide a free licence for personal, open source projects and also to companies generating less than one million dollars in revenue. Their platforms cater for real-time vision processing and batch upload of videos and images to their emotion-as-a-service platform. Each source of frame data is fed into a facial recognition expression engine that is configured to primary emotions and a total of thirty four facial features that include jaw, brow, nose, eyes and lips features. Multiple face tracking has recently been made available, but Affectiva advise that such processing is particularly resource hungry for real-time expression analytics. Affectiva claim that Affdex is currently able to track up to three people in parallel with all facial expressions, emotions and appearance metrics functionality enabled (Affectiva, 2017).

Affectiva actively collaborate with research communities and their work with the Massachusetts Institute of Technology (MIT) Media Lab has produced the Affectiva MIT – Facial Expression Database (AM – FED). The database was developed from users watching a Super Bowl related advertisement. This resulted in a total of 242 facial videos (168,359 frames) being captured during real-world settings. Features used in the dataset include symmetrical FACS action units, asymmetric (unilateral) FACS action units, head movements, smile, general expressiveness, gender, and the location of 22 automatically detected landmark points (Affectiva, 2017). The dataset has received a number of citations including the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2013 (McDuff, et al., 2013) and is freely available for research and non-commercial use.

Affectiva have strong roots in the academic sector and their openness in relation to the Affdex platform has been evidenced during communications with them in relation to this research and related EU research activities. The minimisation of data collected on a subject is a prime focus of Affectiva's privacy policy and no images or videos are stored in the Affectiva cloud for or during frame processing (Affectiva, 2017).

The Emotient FACET SDK (Emotient, 2017) is another leading commercial platform. The SDK detects and tracks expressions of primary emotions, including joy, surprise, anger, disgust, sadness, contempt, frustration, confusion and fear; overall sentiments, including positive, negative and neutral; and blended composites of two or more emotions. The SDK also provides developer access to head pose (yaw, pitch, and roll) and facial landmark points which includes location of eyes, nose and mouth. The SDK and related machine learning algorithms are based on the work of Ekman (Ekman & Friesen, 1978) who has acted as chief advisor to Emotient.

Intel Capital was an original investor in Emotient and up to early 2016, Emotient algorithms were part of the Real Sense SDK. Apple acquired Emotient and since then there has been limited press updates in relation to their strategic intentions for the Emotient platform technologies. iMotions (iMotions, 2017) a provider of biometric multi-sensor research platforms previously integrated Emotient (Emotient, 2017) but their other vision partner relationship with Affectiva is currently taking prominence on their web site (iMotions, 2017).

Researchers at the CIT SIGMA laboratory use multiple versions of the Real Sense SDK including the earlier versions with integrated Emotient vision recognition classes. Emotient is a caution to AC developers to ensure that research innovations are not exclusively locked into any specific provider's platform which could be acquired and indeed removed from availability. At such an early stage in the growth of AC, openness of any development efforts to seamlessly interface with a range of vision platforms is of strategic importance. This openness has been one of the original core design principles of the SenseCare platform (SenseCare Consortium, 2016) which is related to this research, where it will be possible to integrate a range of AC vision sensors (including open source) to mitigate exclusivity to any sole AC vision service/platform.

Kairos (Kairos, 2017) is a dedicated vision provider with API and SDK services focusing exclusively on AC vision, offering emotion analysis, face recognition and cloud demographics. Their SDK provides image and video processing, six core emotions (joy, surprise, sadness, fear, anger, disgust), age, gender and glasses/no-glasses features. Tracking can be used to analyse attention levels and the intensity of direct connection of a subject with the camera. The SDK claims to be able to track up to 20 faces in parallel with 49 facial landmark points (Kairos, 2017). The Kairos API provides both emotion and face recognition analytic services for the creation of AC vision based apps. Kairos is a close match to Affectiva, with face recognition as one of their main differentiators (Virdee-Chapman, 2017).

In conclusion of this technology oriented section, the Glass (Google, 2017) project and Google's re-focus to provide API and development services for partners developing Glass based products is relevant to AC and GCV. According to Wareable (Lamkin & Charara, 2017) there are a range of Glass based and similar products on the market and a number of devices offer features for recording and processing video and images. The original concerns highlighted in relation to Glass (The Center for Digital Ethics and Policy, 2015) safety and security have not constrained manufacturers in producing a range of Glass type innovative devices which will ultimately open up further channels and challenges for image and video processing by AC systems.

This ends the section on the investigation into a range of AC vision related technologies. The next and final section concludes with a discussion on a number of the remaining problems and challenges for AC vision in the future.

### 2.3.3 Discussion on Remaining Problems and Challenges

FACS has played a major role in a number of vision platforms described, but such platforms are facing increasing challenges with demand for real-world, real-time emotion recognition. The limitations and challenges of FACS were highlighted by Calvo and D'Mello (2010) and new approaches using salient facial patches by Happy and Routray (Happy & Routray, 2015) were found to produce performance improvement in conditions where image resolution quality was varied. The recognition of engagement, interest and attention (by a subject) using vision is another challenging area for AC research and will certainly lead to further advancements in areas such as eLearning, GBL, man-machine interfaces and many other domains.

While vision research will continue to evolve, there are core limitations and real-world factors that are clearly evident and will need to be addressed as the field advances. Image quality, resolution, blur, noise and occlusion are ever challenging problems for the computer vision research community. Adding affective analytics into the computer vision technology stack adds a whole new dimension of processing complexity.

For example, when humans communicate together in dual or multi-party scenarios, one party may perform an unusual expression or body movement (turning face away) and this very natural human response could be interpreted as a potentially highly emotional stimulus. This scenario alone highlights the multifaceted nature and the scientific challenges ahead for future developments of AC powered vision adaptors.

Other problems are a mixture of scientific, technological and methodological. From a scientific aspect, personalisation can be expected to lead to customised AC classifiers for specific domains such as eHealth, depression and vehicle navigation as possible future candidates. There is already evidence of this in relation to research being conducted by car manufacturers (Schmidt, Decke, & Rasshofer, 2016). With developments into customised vision based classifiers for specialised application domains, there is then the challenge of engineering personalised classifiers with immutable emotional memory capabilities and learning based on an individual user of an AC platform.

Other scientific challenges include research into the expansion of the emotion set that can be processed from facial expressions. Outside the basic set of emotions, can more complex emotions such as hate, attention, and attraction be processed using vision? What can be learned from micro expressions and how can subtle changes in facial geometry uncover further affective insights. Also further research into cultural variations and ethnic aspects of facial expressions such as JAFFE (Lyons, 2010) is required for engineering AC vision with true fit for a global audience.

Technologically there are new challenges that will surface as AC vision starts to proliferate into every day environments. Image quality assurance and occlusion challenges need to be addressed for real-world environments. Also there may be the requirement to capture video data from different sources (home, work, travel and social) for AC analytics on an individual, perhaps in a security related context. Such a scenario may require interconnection capabilities across multiple sources where video data is captured on a subject. As video becomes increasingly available perhaps new types of video amalgamation services and providers will be required. How is this video data to be shared across all interested and involved organisations? What are the security, ethical and standards issues relating to personal data capture? Realistically all these factors and issues need to be considered and will require serious thought and research if AC vision systems are to transition out of the lab and into real-world domain scenarios.

From a methodological process perspective, the acceptance of AC into everyday activities must not be underestimated. Privacy, anonymity, legal, ethical, moral, safety and duty of care all exist as major challenges if AC vision systems are to be deployed across work places, transport hubs, cities, colleges, hospitals etc. Legislation needs to ensure such powers of personal and cognitive insights on an individual are not utilised in a negative or detrimental manner and this is a challenges that needs to be addressed at this early stage by governments and legislators to ensure a smooth transition of AC into everyday living.

AC vision is truly the first emotion-as-a-service offering and already there are various players, platforms and charging models evolving. Proper methodological clarification of cost frameworks for vision processing is required for organisations such that they can confidently consume AC vision analytics in the engineering of future cognitive applications and services.

The many scientific and technological issues highlight quite a number of problems and challenges that AC vision is facing into the future. Calvo et al. (Calvo & D'Mello, 2010) point out that *additional technological development is necessary before vision-based affect detection can be functional for real-world applications* (Calvo & D'Mello, 2010), [p. 24]. They state that the most important development has been the progress that has been made towards larger and more naturalistic emotion databases (Calvo & D'Mello, 2010).

Poria et al. (Poria, Cambria, Bajpai, & Hussain, 2017) provides further insights into the future of AC vision research directions. They discuss how deep 3D convolution networks (Leng, Liu, Yu, Zhang, & Xiong, 2016) have been *proposed for spatio-temporal feature learning* (Poria, Cambria, Bajpai, & Hussain, 2017), [p. 107] and have developed a convolutional recurrent network to extract visual features. In their research they used stacked convolutional networks on both sentiment analysis and emotion recognition datasets and their approach is represented graphically in (Poria, Cambria, Bajpai, & Hussain, 2017), [p. 108].

Also in their comprehensive literature study they found that *more than 90% of studies reported visual modality as superior to audio and other modalities* (Poria, Cambria, Bajpai, & Hussain, 2017), [p. 118]. On future developments, Poria et al. (2017) write that with the *advent of deep learning research, it is now a viable question whether to use deep features or low-level manually extracted features for the video classification* (Poria, Cambria, Bajpai, & Hussain, 2017), [p. 119] process. They also question if the *ensemble application* of deep learning methods combined with *handcrafted feature* extraction methods can further improve the classification accuracy of video affect recognition technologies (Poria, Cambria, Bajpai, & Hussain, 2017), [p. 119]. Poria et al. (2017) also argue that extensive research is required on the analysis of spontaneous expressions rather than acted expressions in video which should further drive more AC vision research into more practical testing in real-world settings.

With the above outlined problems and challenges for AC vision, there are still other fundamental questions that need to be considered. Is it fair to expect further improvement in AC vision? Can computer vision technologies ever really detect what human eyes can pick up? Can AC vison technology systems perhaps outperform human eyes? Can AC systems actually recognise and detect affective data that is physically non-detectable by human eyes?

In summary, having conducted a scientific and technological SoTA review, and discussed the future problems and challenges of AC vision, there is clearly a requirement for additional sources of vision sensory data in order to increase the sensitivity and specificity of automated affective decision/analytical processes.

The next section introduces another major modality and investigates the scientific and technological aspects of physiological wearable sensory devices used in AC research.

## 2.4 Affective Computing Wearables: Scientific Aspects and Technologies

The International Data Corporation (IDC) (IDC, 2017) predicts wearables shipments will reach 213 million units worldwide in 2020 (International Data Corporation (IDC), 2016). Increasingly smart sensory wearables will provide a vital source of real-world human affect data for AC researchers. This section presents the scientific aspects and technologies that are relevant to wearables for AC research.

### 2.4.1 Affective Computing Wearables: Scientific Aspects

From a scientific perspective, the term physiological computing (da Silva, Holzinger, Fairclough, & Majoe, 2014) is gaining acceptance and it is increasingly being used in the literature with reference to wearables. Physiological computing incorporates research disciplines such as electrical engineering, physiology, psychology, medicine and computing. With reference to AC research, physiological signals are those that can be measured and that also provide an opportunity to evaluate an emotional state.

Some of the main physiological signal measurements (including some already mentioned) relevant to affective science research are listed in Table 2-1 Physiological Signals.

| | |
|---|---|
| **Galvanic Skin Response (GSR)** | Indicator of skin conductivity and is measured via electrodes placed on the skin (Picard, 1997). Skin conductivity is measured by GSR sensors which may also be referred to as Electrodermal Activity (EDA), Electrodermal Response (EDR), and Psychogalvanic Reflex (PGR) (Merriam- |

| | |
|---|---|
| | Webster Medical Dictionary, 2017), (iMotions, 2017). |
| **Electromyography (EMG)** | Small electrodes to measure voltage from a muscle and indicates if and when it is contracted (Picard, 1997). |
| **Blood Volume Pulse (BVP)** | Indicator of blood flow gathered using a technique known as photoplethysmography (**PPG**), which shines infrared light onto the skin and measures its reflection (Picard, 1997). |
| **Respiration** | Sensory devices that stretch as the chest cavity expands with resulting conversion to a digital signal value (Picard, 1997). |
| **Electrooculogram (EOG)** | (EOG): Measuring eye movement (Calvo & D'Mello, 2010). Also known as electrooculography (Oxford Dictionaries, 2017) |
| **Electroencephalogram (EEG)** | Method of measuring brain activity. |
| **Electrocardiogram (ECG)** | Traces electrical activity of the heart. |
| **Fingertip blood oxygen saturation (OXY)** | Fraction of the haemoglobin molecules in a blood sample that are saturated with oxygen at a given partial pressure of oxygen. Normal saturation is 95% to 100%. (Free Dictionary, 2017) |

**Table 2-1 Physiological Signals**

Calvo and D’Mello (Calvo & D’Mello, 2010) discuss the interrelationship between psychology and physiology and explain how machine learning techniques are being applied to the identification of patterns in physiological activity that can be matched with different emotion expressions. AC physiological based wearable devices research is strongly linked with the traditions of physiological psychology and psychophysiology according to Calvo and D’Mello. Due to the importance of this link, it is further explored below.

**Physiological Psychology:** This studies how physiological variables such as brain stimulation (independent variables) affect other (dependent) variables such as learning or perceptual accuracy (Calvo & D’Mello, 2010).

**Psychophysiology:** When the independent variable is a stimulus (e.g., an image of a spider, sad video segment) and the dependent a physiological measure (e.g., heart rate), the research is commonly known as psychophysiology (Calvo & D’Mello, 2010).

Most importantly, the fields of physiological psychology and psychophysiology share the common goal of understanding the physiology of behaviour. For AC research purposes, psychophysiology has most relevance and it extends beyond just emotional processing, and addresses cognitive processes such as perception, attention, deliberation, memory, and problem solving (Calvo & D’Mello, 2010). These cognitive processes are all interrelated with AC problems and challenges and will need to be researched as part of the development of affectively intelligent systems in the future.

Calvo and D’Mello specifically highlight a research review conducted by Andreassi (Andreassi, 2007) in relation to psychophysiology/physiological-based affect detection. Andreassi’s work presents key factors to identify and watch out for when conducting psychophysiology based AC research. These factors are summarised below with reference to the Calvo and D'Mello review paper (Calvo & D'Mello, 2010).

**Law of initial values (LIVs):** This states that the physiological response to a stimulus depends on the pre-stimulus physiological level.

- For example, if a subject is already at an initial high level of physiological response, then a smaller response is to be expected if the stimulus is meant to produce an increased physiological response. Alternatively for the same subject, already at an initial high level of physiological response, then a greater response is to be expected if the stimulus is meant to produce a decreased physiological response.

  Note: According to Calvo and D'Mello, *LIV is questioned by some psychophysiologists, pointing out that it does not generalize to all measures (e.g., skin conductance) and can be influenced by other variables* (Calvo & D'Mello, 2010), [p. 26].

**Arousal measures:** Calvo and D'Mello explain that arousal refers to *quantities that indicate if the subject is calm/sleepy in one extreme or excited in the other* (Calvo & D'Mello, 2010), [p. 26]. In a way arousal is linked with the LIV in that poor performance from a stimulus may occur when a subject's arousal is either too low or too high.

**Stimulus-response (SR) specificity**: Theory that states that for particular stimulus situations, subjects will go through specific physiological response patterns.

**Individual-response (IR) specificity:** IR complements SR and relates to how consistent an individual's responses are to different stimulations.

**Cardiac-body (somatic) features:** Changes in heart responses caused by the body getting ready for a behavioural response (e.g., a fight).

**Habituation and rebound:** Two effects appearing in sequences of stimuli.

- When the stimulus is presented repeatedly, the physiological responsivity decreases (habituation).
- When the stimulus is presented, the physiological signals change and, after a while, return to pre-stimulus levels (rebound)

This review of psychophysiology research is extremely relevant and identifies that variances can exist across sensor signals and that other factors (outside signal noise, body movement etc.) may be relevant to explanations for data variability. This work also highlights the importance and recognition of human individuality and indeed the situational and environmental context of the emotional stimulating event. All such data streams need to be considered in the accurate modelling of emotional states from human psychophysiology sensory signals.

Calvo and D'Mello (2010) point out a further important factor. They recognise the evidence based generality of SR specificity but speculate that *accurate recognition requires models that are adjusted to each individual subject, and [that] researchers are looking into efficient ways of accomplishing this goal* (Calvo & D'Mello, 2010), [p. 26]. Individual emotion based personalisation is certainly one of the overarching goals of AC and is a further indication of the infancy of the field and the challenging research road ahead to produce truly personalised emotionally aware systems and interfaces.

Novak et al. (2012) presented a survey of methods for data fusion and system adaptation using autonomic nervous system (ANS) responses in physiological computing. Their research is a detailed study into various statistical and machine learning techniques and an insight into the current limitations that exist in psychological computing. The authors believe that despite a vast body of literature available on the subject, there is still no universally accepted set of rules that would translate physiological data to psychological states (Novak, Mihelj, & Munih, 2012), [p. 1].

One of the relevant findings in this research is that the *majority of existing data fusion methods in physiological computing (with the exception of principal component analysis and fuzzy logic) is supervised, perhaps because connections between ANS responses and psychological states are still not yet precisely known* (Novak, Mihelj, & Munih, 2012), [p. 17]. The authors believe that this is unlikely to change in the near future and recommend that physiological computing research should focus on supervised data fusion methods using *properly prepared training data that should be verified using nonphysiological measures such as self-report questionnaires or observers* (Novak, Mihelj, & Munih, 2012), [p. 17]. They also state that feature extraction should be based on well-established features already used in the literature and that dimensionality reduction should also be considered in relation to the removal of any irrelevant features.

From a practical perspective, wearable sensors pose multiple challenges such as signal quality assurance, noise cancellation, sensor locations issues in order to provide more accurate affective data analytics. Today there is an increasing body of research taking place on the use of sensory wearables in AC research.

Sakr et al. (Sakr, Elhajj, & Huijer, 2010) conducted research into a novel application for the detection of agitation and the agitation transition phase in dementia care subjects. Wearables were used to monitor the heart rate (HR), GSR and skin temperature (ST) of patients and valuable wearable sensor related insights are discussed. The relevance of the HR signal to agitation detection is explained with reference to the autonomic nervous system (ANS) (Kreibig, 2010). The ANS is made up of the sympathetic nervous system (SNS) (ScienceDaily, 2017) which deals with emergency life situations and is often referred to as the fight or flight response and the parasympathetic nervous system (PNS) (El-Sheikh, Erath, & Bagley, 2013) which is responsible for a relaxed state of being.

Sakr et al. discuss how the activity of the PNS and SNS leads to knowledge about the stress levels of a subject. High PNS activity indicates a relaxed patient and a high SNS activity corresponds to agitation levels in a patient. Stress studies have shown a high correlation between Heart Rate Variability (HRV) (Xhyheri, Manfrini, Mazzolin, Pizzi, & Bugiardini, 2012), PNS, and SNS (Sakr, Elhajj, & Huijer, 2010). When the stress level goes up the moisture level of the body also goes up. This leads to a decrease in the resistance of the skin which consequently leads to an increase in skin conductance (SC) (Hong, Lee, Lim, & Park, 2012). According to Sakr et al. when a person is stressed, blood vessels contract and this leads to a drop in skin temperature. Their work refers to studies in (Kistler, Mariauzouls, & von Berlepsch, 1998) which have shown that skin temperature is at its lowest when a person's stress level is at its highest.

Sakr et al. reduced physiological feature complexity using principal component analysis (PCA) (Ringnér, 2008) and also introduced the concept of a confidence measure $C_{(z)}$ into their classification process. The confidence measure $\mathbf{C_{(z)}}$ was *used to modify a single 2-class SVM classifier into a single 3-class* SVM classifier (Sakr, Elhajj, & Huijer, 2010), [p. 100]. The 3-class SVM was used to predict agitation (+1), non-agitation (-1) and a third transition class called T which was able to detect whether the subject was calm and transitioning to an agitated state or if the subject was agitated and transitioning downwards to a calm state. The Figure 2-16 Decision Rules for Agitation Detection relating to the single 3-class SVM classifier, shows the calculation rules used in the decision making in relation to the agitation state of a subject.

Definition 3. Let ***z*** be an input of unknown class, then:

$$\text{Class} = \begin{cases} -1, & d(\boldsymbol{z}) < 0 \text{ and } C(\boldsymbol{z}) > 0 \\ 1, & d(\boldsymbol{z}) > 0 \text{ and } C(\boldsymbol{z}) > 0 \\ T, & C(\boldsymbol{z}) <= 0 \end{cases}$$

Where "T" is the transitional phase of agitation.

**Figure 2-16 Decision Rules for Agitation Detection**

This research concluded that the use of the confidence measures **C(z)** in conjunction with a SVM produced a higher level of accuracy as opposed to not using **C(z)** in the classification process. The results presented indicate that their agitation detection classifier achieved an accuracy of 91.4%, as against the non-confidence measure based traditional SMV which achieved 90.9%. One other significant finding is the subject-independence nature of their work. The classifier was trained on a limited group of subjects and experiment tests were carried out on subjects not belonging to the original training group.

Work by Ghaderi et al. (2015) used respiration, GSR from the hand, GSR from the foot, heart rate, and EMG physiological data from subjects experiencing different situations and places while they were being monitored while driving. Their research was aimed at stress detection and used K-nearest neighbour (KNN) and support vector machine (SVM) classification algorithms. The research classified three level of stress as low, medium and high and involved the processing of 78 features produced from the above five wearable sensors.

The subjects driving was divided into 100, 200 and 300 second interval states. For the 100 second interval state, the maximum accuracy of the stress level classification achieved 98.41% for the SVM classifier using all five sensors and twenty features. The same rate of 98.41% classification accuracy was achieved for the 200 second interval state also for the SVM classifier, five sensors but with sixteen features. For the 300 second interval state a maximum classification accuracy of 99% was achieved using the KNN classifier, three sensors and only five features (Ghaderi, Frounchi, & Farnam, 2015). Ghaderi et al. provide a full sets of results across the three interval states for both KNN and SVM along with a comparison with other related research and how their results have achieved superior performance to other research in the field.

Research on agitation and stress detection is extremely valuable to healthcare research and considering the global dementia predication figures (Wimo, Jönsson, & Gustavsson, 2009) such AC powered advances are vital in order to cope with the projected demands. Agitation and stress detection is also extremely relevant to the application domains that have shaped this thesis research.

Other research work by Wen et al. (Wen, et al., 2014) relates to multi-variant correlation of physiological signals. Film sequences were used to elicit amusement, anger, grief and fear from subjects. Using the BIOPAC MP150

(BIOPAC Systems Inc, 2017) multi-channel physiological recorder and the AcqKnowledge (BIOPAC Systems Inc., 2017) software, each subject was set up with OXY, GSR and HR wearables. Wen et al. highlight that emotion recognition from physiological sensory signals is a unique pattern recognition problem. They found that *amusement, fear, anger and grief can influence the fluctuations of HR, first derivative GSR (FD_GSR) and GSR at many emotion eliciting film plots, but not significantly affect the fluctuations of fingertip OXY* (Wen, et al., 2014), [p. 134]. A random forest (RF) (Masetic & Subasi, 2016) classifier was used with a total dataset of 477 case data vectors (representing amusement (75), anger (78), grief (98), fear (92) and baseline (134) data sets). The 198 physiological features for each case were made up of 155 HR features plus 43 combined GSR and FD_GSR features.

The researchers claim an overall correct classification rate (CCR) (Brownlee, 2014) of 74% across four emotion states (amusement, fear, anger, grief) and a baseline but point out a difficulty they had in distinguishing between amusement and grief from their physiological feature data. Significantly, their *correlation analysis reveals that multi-subject HR, GSR and FD_GSR fluctuations respectively have common intra-class affective patterns* (Wen, et al., 2014), [p. 126] which is discussed in their research under a section on the similarity of affective physiological data on [p. 131]. They believe that their classification error between amusement and grief is related to the inter-class similarity of multi-subject amusement and grief patterns of the GSR, FD-GSR and HR feature data.

Wearable device validation is increasing in importance and McCarthy et al. present a preliminary study into the *signal quality of the Empatica's E4 portable photoplethysmogram (wearable) device as validation for further research on* *using the device to detect the heart arrhythmia atrial fibrillation* (irregular heartbeat) (McCarthy, Pradhan, Redpath, & Adler, 2016), [p. 1]. They wished to verify the E4 device against a device used by clinicians to detect atrial fibrillation. In the research, the E4 device was compared against the General Electric's SEER Light Extend Recorder holter portable electrocardiogram.

The experiments involved seven participants that agreed to wear both devices for a period of twenty four or forty eight hours. It is noted that the data analysis was conducted by non-clinical experts. McCarthy et al. (2016) report that the primary reviewer's results showed similar data quality between both devices 85% of the time and that the General Electric's SEER Light Extend Recorder holter performed better 5% of the time (McCarthy, Pradhan, Redpath, & Adler, 2016), [p. 4]. This work is interesting and related research that perhaps indicates a shift towards more trusted and clinical validation for wearable devices in the future. The Empatica E4 will be discussed in further detail in the next section on AC wearable technologies.

With reference to sensing and wearable devices for eHealth informatics, Zheng et al. (2014) provide a future perspective and overview of four emerging and unobtrusive wearable technologies. The authors believe that the future in wearables is very much reliant on advances in a number of different areas such as *materials, sensing, energy harvesting, electronics and information technologies for data transmission and analysis* (Zheng, et al., 2014), [p. 1550]. The four main areas predicted by Zheng et al. (2014) are briefly outlined below.

**1) To develop flexible, stretchable and printable devices for unobtrusive physiological and biochemical monitoring:** Developments in flexible, stretchable and printable wearable devices are expected to see possibilities in the future for electronic based skin enhancements and easy to use skin-attachable devices.

**2) To develop wearable physiological imaging platforms, especially unobtrusive ones:** This involves developments that will transform existing one dimension physiological data into two dimensional data whereby spatial information could provide local insights on a subject similar to those already provided by magnetic resonance imaging and ultrasound imaging techniques.

**3) To develop wearable devices for disease intervention:** In this section, Zheng et al. (2014) discuss how wearable devices could be used to prevent a condition or disease. They explain how a wearable artificial endocrine pancreas is used for diabetes management and involves a *wearable glucose monitor and an implanted insulin pump* (Zheng, et al., 2014) [p. 1551]. They also discuss how a wearable drug delivery system for blood pressure management could be developed in the future. While their applications are directly medical related, development in this space will also indirectly impact on AC research and development work.

**4) To develop systematic data fusion framework:** The authors also envision a big data fusion that will integrate the *multimodal and multiscale big health data from sensing, blood testing, bio-marker detection, structural and functional imaging for the quantitative risk assessment and the early prediction of chronic diseases* (Zheng, et al., 2014), [p. 1551]. Again these expected developments in relation to data fusion frameworks will have added benefits and mutual complementarities for the AC research community.

In summary, some of the main points discussed above relate to the specificity and variability of signal data from wearable sensory devices. The identification and generality of patterns in the data used to identify common emotions and the augmentation of such general emotion classifiers with more personalised and informed AC intelligence (with the overall aim of increasing classification sensitivity and specificity) is an indication of what AC scientific research needs to target in the future. Numerous challenges still lie ahead in relation to the transformation of wearable (physiological) sensory data streams into actionable affective intelligence based data for processing by AC systems.

### 2.4.2 Affective Computing Wearables: Technologies

This section provides a review of wearable technologies that have gained recognition through AC research. Empatica (Empatica, 2017) provide a wearable device with EDA sensors. Empatica define EDA as electrical charges *measured at the surface of the skin that arise when the skin receives innervating signals from the brain* (Empatica, 2016). In states of emotional activation, physical activity and cognitive workload the brain sends *signals to the skin to increase the level of sweating* (Empatica, 2016). This activity activates the pores to fill with sweat below the surface which may not necessarily appear on the surface of the skin. As a result, it is changes in the electrical conductance of the skin that enables the measurement of EDA in units known as microSiemens (μS) (ConvertUnits.com, 2017).

Empatica explain that the skin conductance resulting for emotion, physical or cognitive changes is traditionally characterised into two types.

- Tonic skin conductance: Smooth underlying slow changing levels
- Phasic skin conductance: Rapidly changing peaks (Empatica, 2016).

In Figure 2-17 Empatica - High Quality EDA Signal below the top red graph line demonstrates a high quality EDA signal with *exemplary skin conductance responses (SCRs) circled* (Empatica, 2016). The red line indicates the phasic activations while the straight white line is at a smooth level of change indicating the measured tonic skin conductance values.

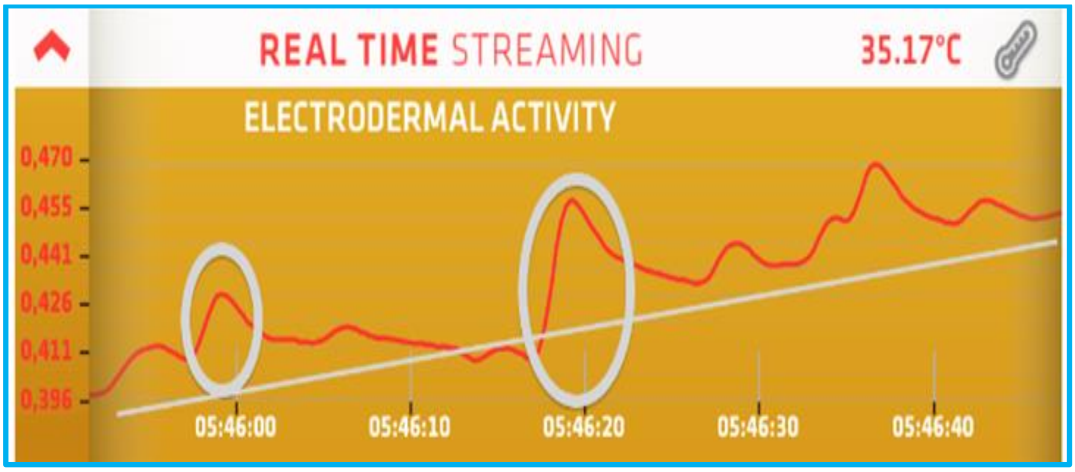



**Figure 2-17 Empatica - High Quality EDA Signal (Empatica, 2016)**

The Empatica E4 (Empatica, 2017) is a dedicated clinical grade wearable sensory band aimed at research communities and is displayed in Figure 2-18 Empatica E4 Wearable. The E4 offers photoplethysmography (PPG) (Allen, 2007) for continuous hearth rate analytics, EDA analytics for GSR, sympathetic activation, autonomic arousal and excitement, an accelerometer for movement data and an infrared skin temperature thermopile.

E4 data can be downloaded using the Empatica Manager (Windows and MAC) and it can also provide live streaming feeds via mobile (iOS and Android) using a number of Empatica developed apps. The Empatica Connect cloud service represented in Figure 2-19 Empatica Connect Dashboard provides access to encrypted data, CSV format downloads, time stamped data and signal comparison graphical services (Empatica, 2017). The Empatica API can be used to develop PC, tablet and mobile apps and mobile SDKs exist for iOS and

Android.  Windows based development requires a separate server for handling E4 client connectivity and data streaming.


**Figure 2-18 Empatica E4 Wearable (Empatica, 2017)**


**Figure 2-19 Empatica Connect Dashboard (Empatica, 2017)**

The Microsoft Band 2 (Microsoft, 2017) focuses on health, fitness and acts as a phone companion for Windows Phones, iOS, and Android.  The Band 2 has nine hardware sensors that developers can access for sensory signal processing purposes. The hardware sensors provide for geographical positioning, ultraviolet monitoring, sleep tracking, calorie tracking, guided workouts, smart notifications and a barometer for tracking elevation changes. Six of the hardware sensors are described in Figure 2-20 Microsoft Band 2 Sensors The Band 2 SDK exposes data from sensor streams which applications can subscribe to.

The Microsoft Health App (Microsoft, 2017) provides both mobile and cloud based access to data collected on the Band 2. The Microsoft Health Cloud API (Microsoft, 2017) is an additional service that uses ReST-based (Richardson & Ruby, 2007) Microsoft Health Cloud APIs. During 2017 Microsoft withdrew the Band 2 from general availability (Microsoft, 2017) and it remains to be seen if they will continue with a hardware and combined software approach for eHealth or perhaps focus exclusively on their health cloud services. Technology press by Bowden from Windows Central (Bowden, 2016) provide an insight into a possible Band 3 prototype with waterproofing, ECG and radio frequency identification (RFID).


| | |
|---|---|
| 1 | Barometer |
| 2 | Heart rate monitor |
| 3 | UV sensor |
| 4 | UV sensor |
| 5 | Microphone |
| 6 | Galvanic skin response (GSR) sensor |

**Figure 2-20 Microsoft Band 2 Sensors (Microsoft, 2017)**

In summary, the Band 2 provides a number of AC relevant sensors and even if Microsoft is stepping back to focus on its software platforms and leaving the wearable innovations to dedicated manufacturers they are still a key technology provider of solutions for AC researchers. The Band 2 has been investigated and evaluated as part of this thesis research. Even though it is not currently a certified medical device (which could act as a limiting factor in its uptake for AC research) it still certainly offers a range of innovative functionality and software development services for a tightly integrated AC wearable device.

Shimmer has released Consensys Software (Shimmer, 2017) for multi-sensor device management. The Figure 2-21 Shimmer Consensys Platform displays an image from the Consensys platform which has been developed to work across Shimmer's kinematic and biophysical sensor products range. The focus of their software suite is on multi-device sensor data collection and multi-subject management both in the field and in the lab. Consensys development kits are provided for Inertial Measurement Units (IMU) (Höflinger, Müller, Zhang, Reindl, & Burgard, 2013) (XSENS, 2017), ECG, EMG and GSR.

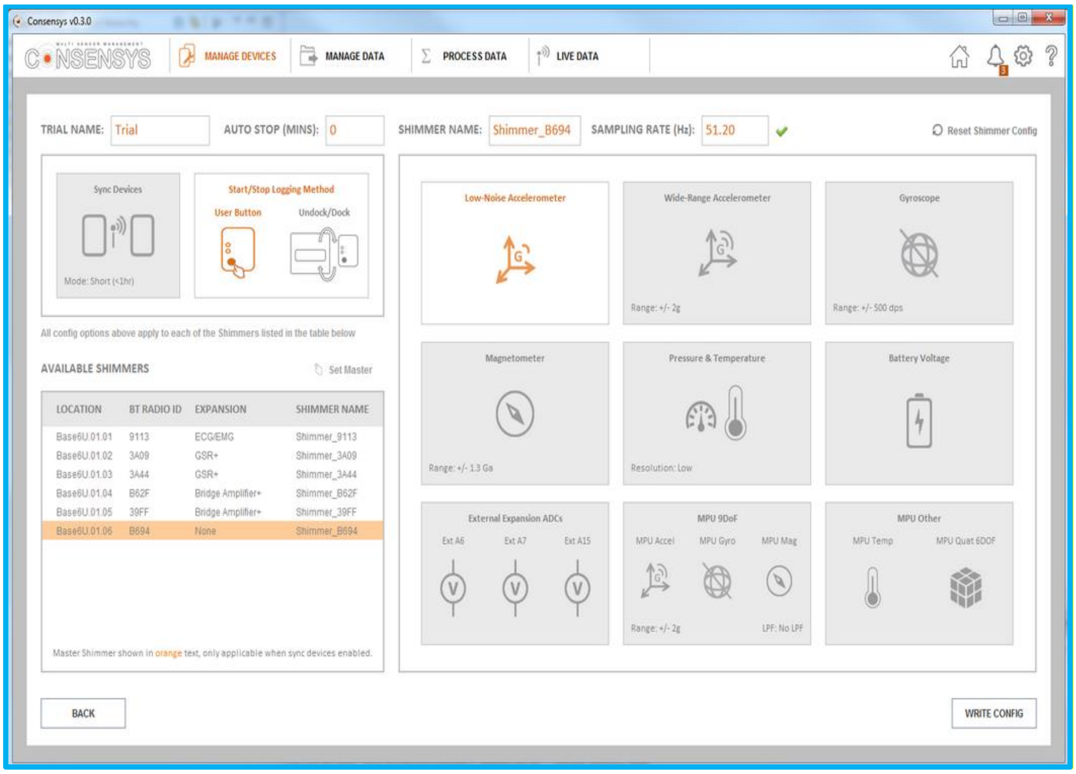



**Figure 2-21 Shimmer Consensys Platform (Shimmer, 2017)**

Shimmer is positioning their Consensys GSR development kit at developers and researchers seeking to monitor physical activity and emotional arousal. The Figure 2-22 Shimmer Consensys GSR Sensor Unit provides details on the development kit GSR sensor unit which provides for the capture of PPG (heart rate variability, stress, relaxation) and EDA (GSR for arousal and excitement). The device also has an accelerometer, gyroscope, magnetometer and integrated altimeter. Developers can manage and access multiple devices with the automated transfer of logged data from multiple sensor devices. Sensor data is stored in an SQL-based database and provides export into CSV and other formats with MATLAB, LabVIEW, Android and C# software development tools available to developers.

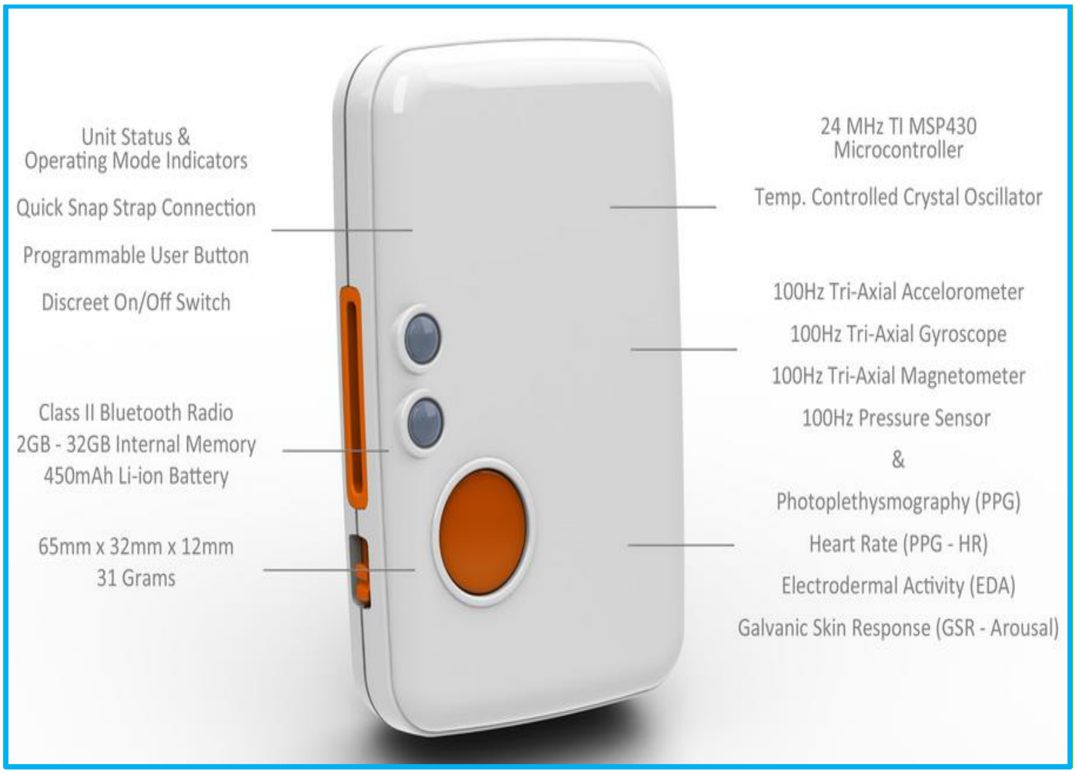



**Figure 2-22 Shimmer Consensys GSR Sensor Unit (Shimmer, 2017)**

In relation to AC, Shimmer conducted a Group Quantification (Shimmer, 2015) experiment involving one hundred viewers of a series of short films. GSR and HR sensory data was measured to track emotional states across the subject group. Shimmer present data investigations for subject #002 and #037 in Figure 2-23 Shimmer Group Quantification GSR and HR. Diagrams (a) and (b) show the GSR (top graph) and HR (lower graph) recorded on both subjects for the entire duration of the recording. The orange lines indicate the start and the grey lines indicate the end of films watched by subjects. The underneath graphs (c) and (d) relate to zoomed in points in the timeline. While the image resolution of the minute times in graphs (c) and (d) may not be quite clear, the whole image has been reproduced in order to demonstrate a marked relationship between the GSR and HR signals for both of the subjects.

For example, and with focus on the lower zoomed in graphs, it can be seen that *instances of a sudden and short-lived increase in heart rate coincide with significant responses in the GSR signal, suggesting that the variation in heart rate is caused by the same stimulus as the GSR reaction. Examples of this effect are evident at approximately 27 mins, 30 mins and 31 mins* (Shimmer, 2015) [p. 5] in graph (c) for subject #002 with the top graph representing GSR and the lower graph representing HR. The zoomed in graph for subject #037 also supports this finding and is displayed at approximately 59.6 minutes in graph (d) where both the GSR and HR also show a visible spike. Shimmer suggests that their group quantification results need additional investigations in a more controlled experiment to further analyse their identified relationship between GSR and HR.

The Shimmer's NeuroLynQ (Shimmer, 2017) is able to measure the emotional responses of up to 36 people simultaneously using scientifically validated GSR and ECG data. Also relevant to AC application domains is their recent partnership with ESSEN to deliver remote patient monitoring in India (Shimmer, 2017). The simultaneous processing by Shimmer's multi-sensory approach combined with back-end data analytics (such as NeuroLynQ) is extremely relevant for AC research. Shimmer is used by researchers worldwide and is referenced in many research publications and conferences (Shimmer, 2017).

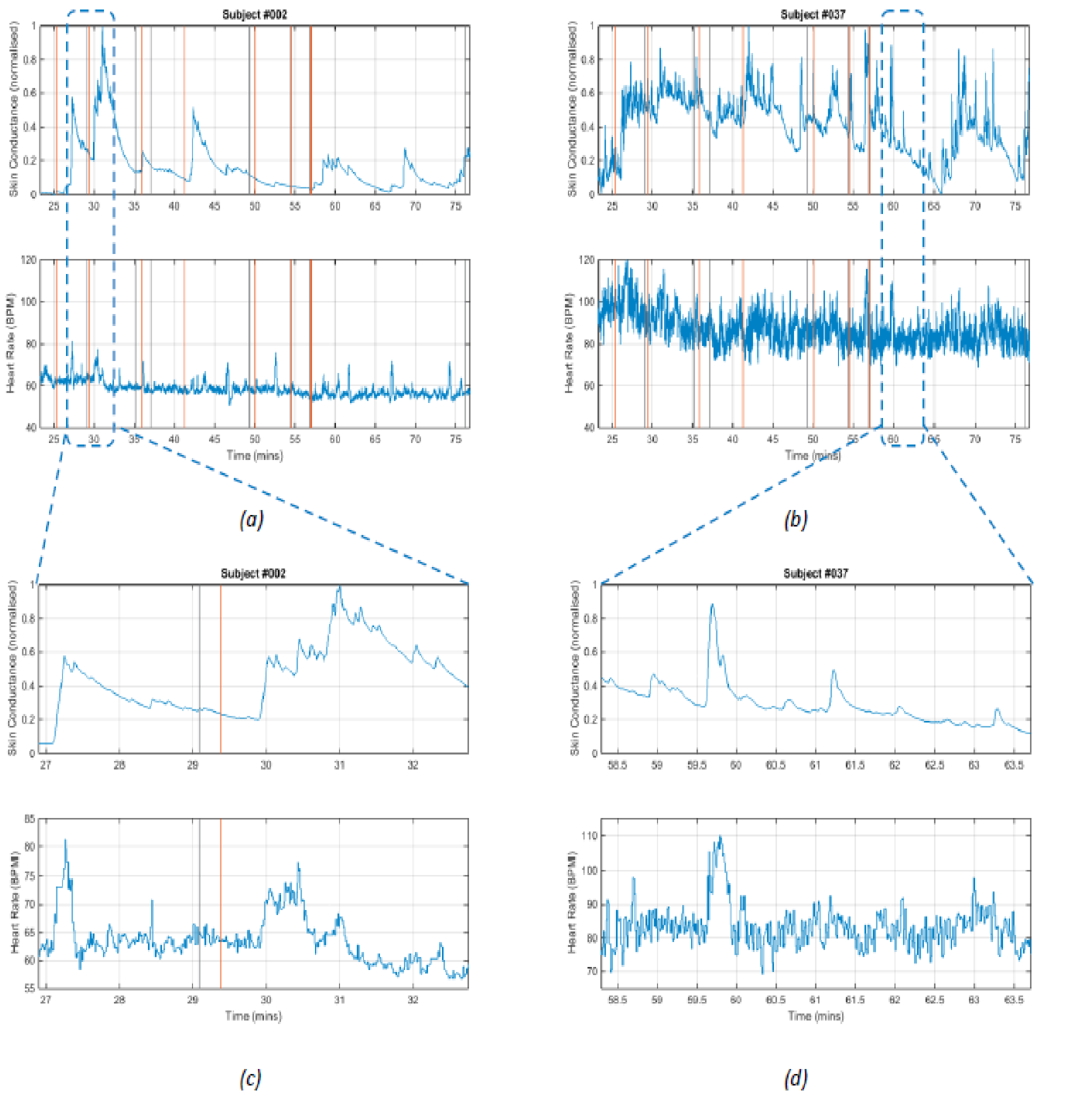



*Figure 4 Skin Conductance (upper plot) and Heart Rate (lower plot) from Subject #002 (a), (c) and Subject #0037 (b), (d). Vertical lines indicate start (orange) and end (grey) times of films. Data are displayed for the entire duration of the recording (a), (b) and zoomed in around a short period during which there are visible responses (c), (d).*

**Figure 2-23 Shimmer Group Quantification GSR and HR (Shimmer, 2015)**

BIOPAC provide dedicated systems for physiological research and was discussed previously in relation to research conducted by Wen et al. (Wen, et al., 2014). The BioNomadix (BIOPAC, 2017) system of wearable wireless devices provides access to a range of signal data including EDA (GSR), ECG, EMG, EOG, pulse, respiration, temperature and cardiac data. The BioNomadix Logger is used to record collected data and also provides GPS and audio notifications. Their AcqKnowledge (BIOPAC Systems Inc., 2017) software provides advanced data analytics with possibilities for recordings of BioNomadix data for multi-subject AC experiments.

The comprehensive range of technologies offered by BIOPAC is far too detailed for this review but one other product stood out with potential for AC research. BioHarness (BIOPAC, 2017) tracks ECG, respiration, temperature, posture, and acceleration. The device is ideally suited for real-world based experiments but it currently lacks EDA sensor data. Bluetooth is used to transmit data to the TEAMSystem-1 (BIOPAC, 2017) which can act in stand-alone single user mode or can be expanded to monitor multiple subjects in real time. BioHarness also works with other BIOPAC analytical software services.

PhysioNet (National Institute of General Medical Sciences (NIGMS), 2017) offers free web access to large collections of recorded physiological signals contained in PhysioBank. According to their website, *PhysioBank contains over 90,000 recordings of over 4 terabytes of digitized physiologic signals and time series, organized in over 80 databases* (National Institute of General Medical Sciences, 2017). There is also a community service called PhysioNetworks (National Institute of General Medical Sciences (NIGMS), 2017) which provides collaborative workspaces for research work in progress. PhysioNet is supported by the National Institute of General Medical Sciences (NIGMS) (National Institute of General Medical Sciences (NIGMS), 2017) and the National Institute of Biomedical Imaging and Bioengineering (NIBIB) (National Institute of Biomedical Imaging and Bioengineering (NIBIB), 2017).

Another interesting device with AC potential is the BioStampRC in Figure 2-24 MC10 BioStampRC Sensor which is produced by MC10 (MC10, 2017). The BioStampRC is a flexible body worn sensor capable of moulding to the contours of the human body. The device has been discussed by the Medical Futurist, Dr. Bertalan Mesko (Mesko, 2017) as relevant to the managing of Alzheimer's and Parkinson's disease (Mesko, 2015).


**Figure 2-24 MC10 BioStampRC Sensor (MC10, 2017)**

According to MC10 the *BioStampRC sensor has multiple configurable sensing modes. Different modes use different combinations of a three-axis accelerometer, a six-axis accelerometer + gyroscope, and a single-lead (two-electrode) analog voltage* sensor (MC10, 2017). This provides for a number of recording modes including ECG, EMG, accelerometer and gyroscope. According to the research conducted, the MC10 focus is on physiological data signals from muscle and body movement and it does not currently support GSR sensors. That said, it is still a very interesting device for AC research purposes and it is a clear indicator of how body wearables are advancing and will evolve in terms of sensor density and inconspicuousness in the future.

### 2.4.3 Discussion on Remaining Problems and Challenges

This section has highlighted the scientific and technological aspects of psychology and physiology in relation to the processing of affective signals from humans. Unlike vision, wearables are quite new entrants into AC research. In the past, customised wearables were developed by research institutes but it has only been in recent years that cost-effective wearable sensors have become available.

Similar to vision, wearables also open up a range of issues and challenges in terms of AC research. IoTs developments are rapidly unfolding as major global players build out their strategies. As part of these strategies, the development of interoperability standards for the communication and sharing of data across wearable devices needs to be addressed. Directly related to this issue is security, where the data captured is at a notably much higher level of personal sensitivity and AC systems and processes must account for this factor in their design and deployment. AC security is a field in itself and an extremely relevant topic but however it is beyond the scope of this thesis.

At a scientific level, the literature reveals that wearables are increasingly being used in AC research but there seems to be a lack of foundation and real understanding of how emotions are represented by physiological signals. The work of Andreassi addresses the uniqueness of the individual and the interplay between cognition and physiology. Wearables are the technological tools that are aiding the journey into better understanding of affect from physiology, but this area is still in its infancy and it is expected to be some time before a framework similar to FACS can be developed for physiological sensory expression data.

This area of new AC knowledge is a key scientific and technological challenge and driver for the future. For example, new findings by Picard et al. (2016) put forward a theory of multiple arousal. Their research presents evidence that emotional arousal when measured as *sympathetic nervous system activation through electrodermal activity (EDA), can sometimes differ significantly across the two halves of the upper body* (Picard , Fedor, & Ayzenberg , 2016), [p. 1].

The research argues that traditional measures taken on only one side of the body may lead to the misjudgement of arousal. Picard et al. (2016) accept that their work is at a very early stage and further research is required, but the acceptance that using multiple measurements of EDA arousal will produce more *systematic mapping between the space of emotional experiences and measurable patterns of emotional arousal* (Picard , Fedor, & Ayzenberg , 2016), [p. 12] will certainly benefit affective computing research in the future.

Picard et al. (2016) have been challenged in the literature and they have responded to commentaries on their multiple arousal theory. In their rebuttal response they outlined further evidence in relation to varying EDA data from different body sensor location sites. In summary Picard et al. (2016) agree with their critics in that AC research using EDA type wearable devices has opened up many new questions and issues for researchers across AC related disciplines. They point out that the traditional EDA *one-sided measurement, and assuming it will increase with high arousal and decrease with low arousal, is not the whole story* (Picard, Fedor, & Ayzenberg, 2016), [p. 8] and that scientists trying to figure out arousal are still very much working in the dark with arousal being treated similar to a black box phenomenon. Their rebuttal paper specifically states that the tracking of multiple sources of arousal from a subject and the measurement of the resulting distinct data output patterns from such sources may lead to a more informed understanding of arousal and its relationship to emotional experiences.

The asymmetrical aspects of wearables indicate how new knowledge is being garnered as AC research advances. This then asks the questions, what about the sensitivity and specificity of sensory data; can the data collected from sensory devices be fully trusted? For example, research experiments conducted on heart rate monitoring from wrist worn devices were reported by Harvard Health Publications (Harvard University, 2017). The research conducted measured the heart rate from a number of selected wearable devices against the gold standard of an ECG machine value for fifty young healthy adults. They found that the *Apple Watch and the Mio Fuse, were accurate about 91% of the time* (Harvard University, 2017), while the other two wearables, the Fitbit Charge HR and the Basis Peak *were accurate about 84% and 83% of the time* (Harvard University, 2017). The recommendation is that if the exact heart rate value is medically important for an individual then a chest strap type monitor should be used. The exactness requirement of the heart rate value may vary pending the type of AC experimentation but this factor needs to be considered in the wearables equation.

In addressing this challenges of trust in wearable technologies and their related sensory data there is a need to establish a recognised standards based certification process for devices such as the Empatica E4 certification which currently stands as CE Cert. No. 1876/MDD (93/ 42/EEC Directive, Medical Device class 2a), FCC CFR 47 Part 15b IC (Industry Canada) and RoHS (Empatica, 2017). In fact, in February 2018 the Empatica E4 related Embrace device received full FDA approval as a certified medical device (Empatica, 2018).

Personalisation also appears in the wearables literature along with the realisation that human biology is so different at an individual level and that indeed it may never be possible to develop a one size fits all classification model of physiological signals for affect. With this in mind, should such a quest for a common model be abandoned and should AC wearable research advance with personalisation as its underlying theme? These are research questions and challenges that must be addressed in order to develop some form of commonality in taking AC wearables research forward and into the future.

Other technological challenges and issues exist in terms of everyday usage and may impact on how a user's sensory data is presented. These issues include the filtering out of unrelated noise and signal interference artifacts that exist in the sensing environment. Also, everyday considerations such as body movement/activity, illness, medical conditions, personal disabilities, and drugs/alcohol/medication may all cause corruption and/or confusion in the sensory data being processed by AC systems.

Where are the best placement locations for wearable sensors on the body? What are the ergonomic form factors in terms of continual usage and their related implications? Will body worn and embedded sensors with inductive power transmission (Wireless Power Consortium, 2017) and Wi-Fi connectivity have health and safety implications for users. See Clare et al. (2015) in relation to how inductive power transmission aspects are being researched today (Clare, Worgan, Stark, Adami, & Coyle, 2015). In order to properly advance the field, all of these question and challenges will eventually need to be addressed by AC researchers from a technological, legal, ethical and social perspective.

The challenges of ethical, moral and social responsibility also arise in relation to the invasiveness of wearable technologies. Specifically in relation to the possibilities of always-on physiological data tracking, there is a need to consider the psychological, therapeutic and indeed the non-therapeutic aspects of such availability and the possible impacts in terms of self-diagnosis and misuse of such data. Other likely challenges in relation to AC wearables include the fusion aspects of multiple wearable devices and established integration standards for mobile/cloud platforms and eHealth data vaults.

Already sensors are being embedded into items of clothing (Sawh, 2017) and perhaps moving such sensors into beds, cars, computer interfaces and many other objects that the human body interfaces with during the day may be a harmonising research direction for physiological data capture in the future. With physiological data from wearable sensory networks and everyday objects interacting with the human body, it can be expected that there is going to be a major data amalgamation challenge/opportunity on the horizon. Resulting affective data from a myriad of physiological related sensory sources will ultimately have to be fused together to form an overall affective assessment/evaluation of an individual.

The next section of the SoTA chapter compiles research that has been conducted into a number of other sensory modalities (that do not directly fall under the vision or wearables categories) that are increasingly being referenced in the AC literature.

## 2.5 Other Affective Computing Sensors

Vision and sensory wearables tend to be the main scientific techniques and technologies used to capture the data required to make an affective classification/judgement. This section provides investigations across a range of other sensor modalities that are emerging as sub-fields of AC research both academically and commercially.

### 2.5.1 Other Affective Computing Sensors: Scientific Aspects

This section introduces the scientific aspect of a range of other sensor modalities for AC research such as keyboard and mouse input devices, sentiment analytics, gait/body language, and voice. EEG devices could fit into the wearables category but due to the uniqueness and early stages of this technology in AC research it is covered in this section.

**Keyboard and Mouse:** Human interaction with computational systems provides a valuable resource and ever increasing digital sources present ample opportunity for harvesting affective data. The increasing demand for the tracking and monitoring of stress (European Agency for Safety and Health at Work, 2014) relates to the future application domain scenarios already discussed. Vizer et al. (Vizer, Zhou, & Sears, 2009) explore computer keyboard inputs for the identification of acute or gradual changes in cognitive and physical function. Their research aimed to identify if changes in typing and linguistic features had a correlation with changes in the stress level of a subject. Their hypothesis proposed that normal interaction via keyboard could provide insights into medical conditions that could be addressed well before they would be picked up using traditional clinical testing mechanisms. Their use of existing keyboard pattern matching technologies used traditionally for security applications is an interesting pointer for AC researchers where existing systems could be modified to capture/reveal affective and cognitive related data.

Machine learning algorithms were used (Decision Trees (DT) (Brownlee J. , 2016); SVM; k-Nearest Neighbours (kNN) (Brownlee, 2016); AdaBoost (Brownlee, 2016) and an ANN to classify both cognitive and physical stress situations. AdaBoost produced the best overall performance on the raw data in the classification of both cognitive as 61.5% (0.615) and physical stress 62.5% (0.625). When the data was normalised the kNN produced the best classification result for cognitive stress of 75% (0.750) with the ANN and the SVM both achieving 62.5% (0.625) as the best performers for physical stress (see page 879 in (Vizer, Zhou, & Sears, 2009)).

One of the key research questions proposed by Vizer et al. (2009) was to find if machine learning methods could be used to classify free text as being produced under no stress, cognitive stress, or physical stress conditions (Vizer, Zhou, & Sears, 2009). Their results indicate positive evidence for this question. The authors compare their classification rate for cognitive stress to those obtained using AC techniques for stress detection and argue that the keyboard as an affect modality requires no additional hardware, is unobtrusive and is less computationally intensive.

Kahn et al. (Kahn, Kahn, & Shafi, 2012) also used keyboard along with mouse interaction to measure user mood using ANNs. Supervised learning was used to train individual personalised feed-forward ANNs for each subject in their study. Their research results concluded *an average recognition rate of 64.72% for valence and 61.02% for arousal ratings* (Kahn, Kahn, & Shafi, 2012), [p. 130]. The personalisation aspect of their research relates back to previous discussions and could also provide an opportunity for the interchange of ANNs across the participant cohort. This opens up the possible evaluation of how a personalised ANN from participant X performs in a non-personalised manner on participant Y.

This research on inconspicuous inputs based affective analytics can be generalised to user interactions with varying forms of computational and technological objects. Further research into the affective scientific aspects of human to object emotional interactions is required and can be expected to advance at an increasing rate fuelled on by IoTs developments and investments.

**Linguistic based sentiment analytics:** Nguyen et al. (Nguyen, Phung, Dao, Venkatesh, & Berk, 2014) conducted content analysis of social media and used machine learning techniques to classify blog posts from online communities and also the type of online communities. They used the binary classification of clinical to refer to online depression and mental illness communities and control for any other type of online community.

Two classifications tasks were defined:

- **Blog post classification:** For a selected blog post, the classifier decides if the blog is to be assigned a classification of clinical (indicating a relationship to online depression and mental illness communities) or to be assigned a classification of control (indicating a relationship to any other type of online community).
- **Community classification:** This involved the classification of online communities as either being assigned to the clinical or control classification from the analysis of the types of posts on their site.

As part of their research, specific AC related tools explained in their paper (Nguyen, Phung, Dao, Venkatesh, & Berk, 2014), [p. 219 – 220] were used and are represented in the Figure 2-25 ANEW Usage - Clinical and Control Groups:

- Affective Norms for English Words (ANEW) (Bradley & Lang, 1999),
- Mood tags (Mood) used in LiveJournal (LiveJournal Inc, 2015),
- Linguistic Inquire and Word Count (LIWC) package (Pennebaker, Francis, & Booth, 2007)

- Topic identification from words that used latent Dirichlet allocation (Topic) (Blei, Ng, & Jordan, 2003), (Griffiths & Steyvers, 2004).

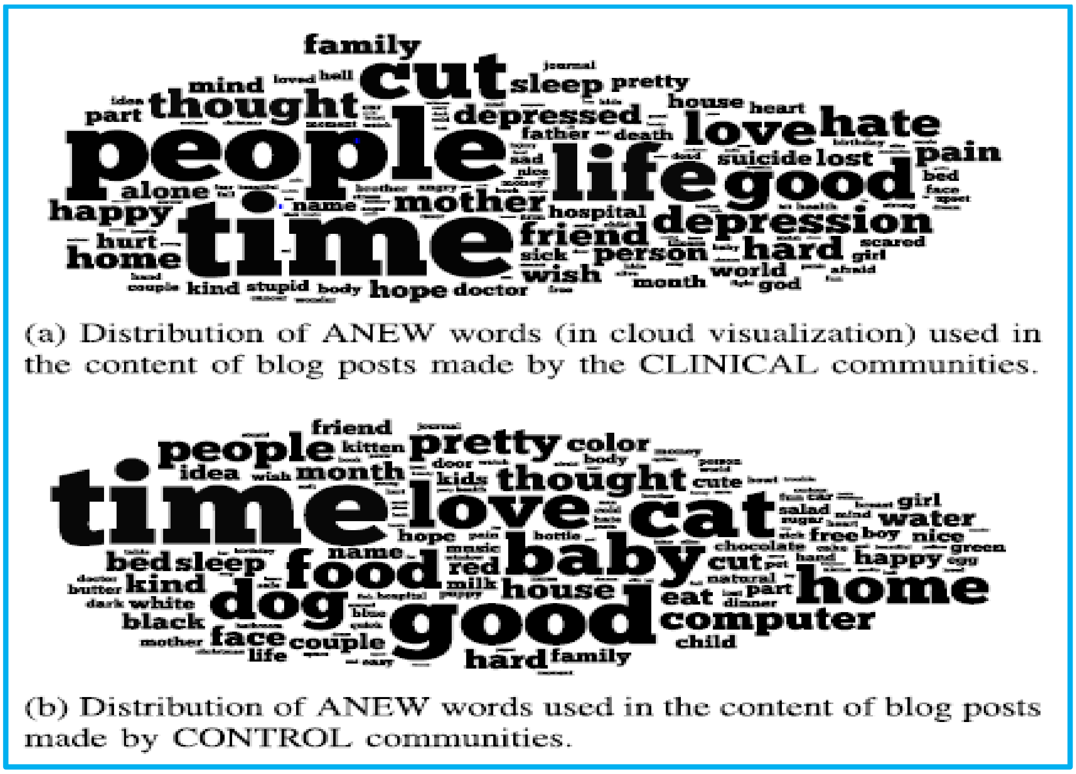



**Figure 2-25 ANEW Usage - Clinical and Control Groups (Nguyen, Phung, Dao, Venkatesh, & Berk, 2014)**

Results reported for community classification is 100% for feature sets created using Topic identification and LIWC, and showed 96% for Mood tags and 89% for ANEW, respectively. Only Topic extraction and LIWC were used for the blog classification which also achieved CCR rates of 93% for Topic and 88% for LIWC, (see Table 4 and 5, (Nguyen, Phung, Dao, Venkatesh, & Berk, 2014), [p. 222]).

Nguyen et al. have produced extremely valuable research in the use of machine learning and related statistical techniques to classify linguistic features from online content for depression and suicide ideation. They conclude that all aspects of *affect, the written content and writing style were found to be significantly different* (Nguyen, Phung, Dao, Venkatesh, & Berk, 2014), [p. 224] between both groups. As social media controversies are likely to increase, providers can be expected to come under ever increasing legislative obligations and responsibility (Bertot, Jaeger, & Hansen, 2012) for their users and content. Linguistic based affective sentiment analytics offers opportunities to address social, ethical, legal and political issues for media providers and could also create new commercial offerings and information services.

**Gait and body language:** Gesture, posture and body language can generally be classified under the field of gait analytics. Researchers working on gait analysis believe that it may also provide a means of affect recognition from a distance (Karg, Kühnlenz, & Buss, 2010). Karg et al. see possible applications for affective gait analysis in human-robot interactions, smart homes/buildings, and high-security locations (e.g., airports). *Classification of gait patterns is challenging for techniques from machine learning, because data of gait recordings are high dimensional, time dependent, and highly variable, and gait variables interact in a nonlinear relationship* (Karg, Kühnlenz, & Buss, 2010), [p. 1053]. The experiments conducted used actors with activity markers and this has resulted in the development of an affective gait database.

Like other AC modalities, limitations naturally exist as full body posture may not always be in view. In relation to challenges, Karg et al. (2010) position affective gait analysis as an additional modality for multi-modal recognition of affect, specifically relevant to long-distance recognition. The results from the research indicate that affective states can be identified using machine learning techniques in the observation of a single stride. The recognition of affect from walking is found to be heavily influenced by individual walking styles and expressions of affect. Person-dependent recognition reached accuracy above 90% for the four affective states of neutral, happy, sad and angry in the acted trials conducted.

Many future areas need to be addressed such as spontaneous affect, multi-gender research, age, weight and physical disorders. Developments using vision systems such as the Kinect and Real Sense full body and depth cameras will lead to future innovations around affective gait analysis. While the universality of FACS is well established in the facial analytics community, the work of Karg et al. (2010) is a reminder of the sheer complexity of trying to develop a similar universal oriented model of gait analytics for affect detection. The challenges ahead certainly justify affective gait analytics as a scientific sub-field and one that could directly compliment facial vision based AC systems, specifically when facial occlusion occurs or a subject is distant from a camera.

**Voice analytics:** Voice (speech) is already an established AC research field with both affective and non-affective applications. Speech and gestures based research addressing human to human stress recognition from interactions at a service desk was carried out by Lefter et al. (Lefter, Burghouts, & Rothkrantz, 2016). Specifically in relation to speech they measured how stress was conveyed by the spoken word (speech semantics stress) and also how stress was conveyed by the way the message was spoken (speech modulation stress). The valence and arousal scores for speech were computed with reference to the Dictionary of Affect in Language (DAL) (Whissell, 1989) and the ANEW (Bradley & Lang, 2017). Using audio and visual data sets it was concluded that speech modulation was the most dominant feature in the communication of stress for service desk scenarios. Gesture analytics certainly have a role but Lefter et al. (2016) found that they did not lead to any significant improvement in the recognition of stress with the exception of some special cases they observed.

Wang et al. (Wang, An, Li, Zhang, & Li, 2015) used Fourier analysis (Rouse, 2005) for their work on speech digital signal processing for filtering and feature extraction. This work created Fourier Parameters (FPs) (WolframAlpha, 1999) from the speech signal and results conclude that FPs are effective in the recognition of specific emotions in the speech signal (happy, bored, neutral, sadness, angry, anxiety). The following three specialised speech emotion databases were used in this research, German emotional corpus (Emo-DB) (Burkhardt, Kienast, Paeschke, & Weiss, 2017), Chinese emotional database (CASIA) (Bao, Li, & Gu, 2014) and the Chinese elderly emotional speech database (EESDB) (Tao, Wang, Yang, An, & Li, 2015).

**EEG analytics:** Blaiech et al. (Blaiech , Neji, Wali, & Alimi, 2013) conducted emotion recognition using an EEG headset in conjunction with a facial detection system for user identification and profiling. The SAM manikin, Geneva Emotion Wheel (GEW) and questionnaires were used for self-reporting in their research. Neuroscience literature identifies six standard EEG bands that differ by their order of frequency as delta, theta, alpha, mu, beta, and gamma. The most specific wave bands for emotion identification are the alpha (8 - 13 Hz) and beta (13 - 30 Hz) bands. Blaiech et al. (2013) used these bands in the computation of arousal, valence and dominance emotion features. After MATLAB (The MathWorks Inc., 2017) filter processing, the feature values were fed into a fuzzy classifier using the Simulink fuzzy logic controller library (MathWorks, 2017). Blaiech et al. defined thirteen fuzzy rules that classified seven emotions and achieved recognition rates of Joy (85.71%), Disgust (85.71%) and Anger (64.28%) as represented in Figure 2-26 EEG Emotion Recognition Rates . The remaining four emotions require further research to increase the CCR according to the authors. It is noted that the accuracy rates and the fact that Joy and Disgust are identical may be a function of the limited sample size of six research participants. This is early stage research and clearly sample size will also need to be addressed.

| Emotion | Recognition rate |
|---|---|
| Neutrality | 57,14% |
| Joy | 85,71% |
| Sadness | 53,57% |
| Fear | 53,57% |
| Anger | 64,28% |
| Disgust | 85,71% |
| Surprised | 53,57% |

**Figure 2-26 EEG Emotion Recognition Rates (Blaiech , Neji, Wali, & Alimi, 2013)**

Jenke et al. (Jenke, Peer, & Buss, 2014) reviewed 33 studies on EEG feature extraction methods for emotion recognition from EEG signals. Machine learning techniques were used to evaluate the various *feature selection methods, usage of selected feature types and the selection of electrode locations* (Jenke, Peer, & Buss, 2014), [p. 327]. Features are generally calculated from the recorded signal of a single electrode but also other features may be the result of a combination of signals from multiple electrode signals (see (Jenke, Peer, & Buss, 2014) section 2, [p. 328]). Feature space is paramount due to dimensionality and using machine learning techniques this research concluded preference to the following advanced feature selection methods, Higher Order Crossing (HOC) (Petrantonakis & Hadjileontiadis, 2010), Higher Order Spectra (HOS) (Hosseini, Khalilzadeh, Naghibi-Sistani, & Niazmand, 2010) and Hilbert-Huang Spectrum (HHS) (Hadjidimitriou & Hadjileontiadis, 2012), (Jenke, Peer, & Buss, 2014), [p. 337]. The research also suggests that for EEG electrode placement *preference* *to locations over parietal and centro-parietal* (Merriam - Webster Medical Dictionary, 2017) *lobes* (Jenke, Peer, & Buss, 2014), [p. 337] should be given. This research is a valuable contribution in the guidance of future EEG related AC research, specifically in relation to feature dimensionality reduction and electrode placement.

Having presented a scientific perspective across a range of other sensors, the next section revisits a number of the above AC sensor modalities from a technological viewpoint.

### 2.5.2 Other Affective Computing Sensors: Technologies

This section expands the state of the art discussion into the more practical aspects of other AC sensor technologies. While this section is in addition to the main focus of the thesis research on vision and wearables, an overall understanding of other sensor technologies available to capture alternative sources of affective data is important in order to fully appreciate the complexity of the AC problem and in particular the multi-sensory fusion aspects of the prototypical solution discussed throughout the remainder of the thesis.

**Gait and body language technologies:** Developments in depth camera technologies and their related SDKs offer many opportunities for research into affective gait analytics. The Real Sense camera version identity R200 (Intel, 2017) provides up to 3.5 meters indoors and this range may be longer outdoors according to Intel. The ZR300 (Intel, 2017) offers ranges greater than 3.5 meters indoors and outdoors but Intel advise that the middleware has been optimised for indoor usage and has not been tested in outdoor conditions. Intel's Euclid (Shah, 2017) shown in Figure 2-27 Intel Euclid is a small handheld computer that comes with a built-in 3D depth camera and Real Sense technology on-board and offers potential for many forms of unobtrusive gait and body language detection.


**Figure 2-27 Intel Euclid (Intel, 2017)**

Intel seems to be initially positioning Euclid as the eyes and sensing capabilities of a robot (Intel, 2017). Depth cameras will certainly become ubiquitous in the coming years and can be expected to be embedded into a range of everyday objects. High-end security surveillance and eHealth can be expected to be some of the main drivers of gait and body language affective analytics technologies.

**Linguistic sentiment analytics technologies:** Linguistic based sentiment technologies can be used to mine and analyse user community emotional related feelings, typically in feeds from Google, Facebook, Twitter, emails or any source where there is a compilation of linguistic text based data. Lexalytics (Lexalytics, 2017) provide research and technologies aimed at discovering people's feelings in relation to particular topics. Salience is their software platform which performs social slang and sentiment analysis as well as categorisation, entity extraction, intention analysis, and topic extraction which can all be used to extract affective indicators from text based streams and documents. IBM Watson Analytics for Social Media (IBM, 2017) is another platform focused around media forms and has the potential for research into affective interaction across social media platforms. These are but two platforms for sentiment analytic services that may be customised for AC research. In the future, this may result in more specialised linguistic oriented affective analytical services targeting bullying, depression, obesity, and addiction as examples of highly relevant target domains.

**EEG technologies:** The Emotiv (Emotiv, 2017) Insight is a dry sensor 5-channel, wireless EEG headset that records brainwaves and translates them into meaningful data. Emotiv also provide a more advanced headset, the Epoc+, which is a 14 channel wireless EEG headset and is designed for researchers and advanced brain computer interface applications. Emotiv have developed emotion related detection algorithms that can measure Excitement (Arousal), Interest (Valence), Stress (Frustration), Engagement/Boredom, Attention (Focus) and Meditation (Relaxation) (Emotiv, 2017). Figure 2-28 EMOTIV EPOC+ and Insight presents images of both Emotiv headsets.


**Figure 2-28 EMOTIV EPOC+ and Insight (Emotiv, 2017)**

NeuroSky provide the MindWave (NeuroSky, 2017) EEG headset and work with other equipment manufacturers to develop domain specific applications using embedded NeuroSky technologies. NeuroSky have developed a number of applied algorithms that are relevant to AC related EEG research (NeuroSky, 2017).

**Pleasant/Unpleasant algorithm:** Identifies whether a user is having a pleasant emotion (happy, serene, and relaxed) or an unpleasant emotion (anger, disgust, depressed).

**Intensity algorithms:** Measures how strong a user's emotions are in real time.

**Alertness algorithm:** Measures alertness or vigilance. High alertness values indicates a user is in a state of focus while low values represent a relaxing state of mind.

Chaudhary et al. claim that *brain computer interfaces based on neuroelectrical technology (like an electroencephalogram (EEG)) have failed at providing patients in a completely locked-in state with means to communicate* (Chaudhary, Xia, Silvoni, Cohen, & Birbaumer, 2017), [p. 2]. Their recent research focused on four patients with locked-in syndrome and used an alternative approach.

They used a brain computer interface based on functional near infrared spectroscopy (fNIRS) (Ferrari & Quaresima, 2012) which measures brain hemodynamic (Hemodynamic Society, 2017) responses associated with neuronal activity. Of significance is the fact that using the fNIRS approach patients were able to *answer personal questions with known answers and open questions requiring a "yes" or "no" by using frontocentral oxygenation changes* *measured with fNIRS* (Chaudhary, Xia, Silvoni, Cohen, & Birbaumer, 2017), [p. 2].

While this locked-in and fNIRS related technological research does not immediately conjure up relevance to AC, it is included here to emphasise the very early stages brain computing interface technologies are currently at. It highlights that EEG along with fNIRS and other techniques are advancing with applied research into brain science and new development and technologies yet to come will possibly see brain computer interfaces having a much more dominant agenda in relation AC and AS research.

**Voice technologies:** Voice is one of the natural sources of affect but it is still a challenging area in terms of research into emotional intonations. audEERING (audEERING, 2017) are a pioneering provider of AC technologies involving the human voice. audEERING develop intelligent audio analysis algorithms that use an open-source speech and emotion analysis framework called open-**S**ource **M**edia **I**nterpretation by **L**arge feature-space **E**xtraction (openSMILE). Their main focus is on audio-signal features extraction but the platform can also be used to analyse physiological, visual, and other types of sensor signals. The platform is written in C++ with code versions available for Linux, Windows, and Mac. openSMILE as a cloud service can process audio streams in real-time and can also be used in off-line batch processing mode for larger data-sets.

audEERING have developed a more specialised platform for the detection of affective states from voice, called sensAI-emotion. sensAI-emotion detects basic emotion categories like joy, anger, fear and emotional dimensions for valence and arousal and has potential applications in *call centres, advertising, virtual agents and humanoid robots* (audEERING, 2017). An interesting eHealth related system developed by audEERING is Audiary (audio diary) (audEERING, 2017) which is a form of assistive technology for patients making notes about their daily routines for medical professionals. Audiary is different from other speech recording tools in that it uses *audEERING's sensAI-emotion technology which offers a complete analysis of the user's (patient's) emotional state* (audEERING, 2017) from the recordings.

**Internet of Things:** One of the research actions of the IoTs relates to the provisioning of information processing/reasoning, potentially covering self-organising systems and autonomous behaviour (European Commission, 2017). This is an opportunity for affective science and computing to be applied specifically to the emerging field of personal care robotics and other interacting objects. Pepper is an emotional robot created by SoftBank Robotics Corporation (SoftBank Robotics Corporation, 2015) that can read emotions as well as recognise tones of voice and facial expressions in order to interact with humans. The robot has an array of cameras, touch sensors, accelerometer and other sensors as inputs to an embedded multi-layer neural network. Perhaps the world is not yet ready for affective interactions with inanimate objects, but projections for robotics entering the workplace and everyday activities are quite real (Business Insider, 2015) and perhaps in time humans will demand some form of intelligent affective based interactions with robotic assistants/workers.

Related to IoT and computer inputs is the physiological mouse (Fu, VaLeong, Ngai, Huang, & Chan, 2014). This uses a PPG signal sensor in everyday mouse driven scenarios to capture physiological signals. The emotion-aware mouse algorithms were evaluated, and results indicate error rates of 2 to 3% for heart rate and just over 5% for respiratory rate analytics as against traditional means of signal recording. Simple, effective and easy to use, development in this area could see next generation mouse devices as an extremely effective sensor for AC data capture. One note of caution is in relation to the previous discussion on wearables, where the true medical accuracy of such sensors must always be verified against clinical grade sensory devices for physiological measurements.

Apple has been granted a patent for a touch pad type device capable of simulating textures and temperatures (Patently Apple, 2016). Such a device if it ever reaches the market could be a possible technology for use in AS and AC research into touch and emotion. Ebe and Umemuro (Ebe & Umemuro, 2015) have conducted research into the use of texture for emotion stimulation and the relationships between texture and emotion. The authors demonstrated how *six dimensions of texture characteristics can be associated with emotions evoked or conveyed* (Ebe & Umemuro, 2015), [p. 1999]. They believe that possibilities exist for using texture as a *communication media for emotional information* (Ebe & Umemuro, 2015), [p. 1999] in the future and that further research should be carried out in relation to this aspect of AC.

Emotion aware robots, textures and touch devices are but a current selection of the potential IoTs powered sensory devices that may infiltrate AC research and development. Such innovations are most likely to create individual but interrelated theories, models and new knowledge that may ultimately contribute towards increased awareness and understanding of the complex computing challenge of human affect.

**Other technologies:** One other final technology encountered during the literature review was that of genetic engineering which may well have a role to play in the future of AC. According to Nature, *people with a particular gene* *variant are better at remembering emotionally laden memories than people with the more common version of the gene* (Smith, 2007). The gene is known as ADRA2B (Genetics Home Reference, 2017) and it is involved in detecting brain chemicals related to emotional arousal. Nature reports that *ADRA2B is involved in the transport of a chemical called noradrenaline in the brain and that people with the variant version of the gene show an increased movement of this chemical between brain cells, a process that is linked to emotional arousal* (Smith, 2007).

Following the above investigation into a number of specific technology based products and services, the final part of this section discusses remaining problems and challenges relating to the other sensor modalities that have been discussed.

### 2.5.3 Discussion on Remaining Problems and Challenges

One of the main issues in the many new forms of modalities is that the harvesting of affect may be unseen or subtle and not immediately obvious to a user. This is very much the case in relation to affective text analytics or computing based inputs. The scientific aspects of other modalities are advancing and a major concern is that computing algorithms may be harvesting and evaluating a person both emotionally and cognitively quite unknown to themselves in the future.

User interactions with everyday objects and how affective states can be captured is an interesting challenge from both the scientific and technological aspects of AC. This has been discussed with reference to everyday technology inputs (PC) but expanding this to emotion robotics, interaction by touch (handshakes and feeling), and smell are all components of the complex mix that feeds and stimulates the emotional states of humans.

Furthermore, humans interact with varying types of objects on a daily basis and there is the need to research and develop theories and network models as to how affective states are impacted, changed or altered from such interactions. Increasingly emotional robotics, carebots (Muoio, 2015) and softbots (Zwass, 2017) will be interacting with humans for many types of activities and such computationally intelligent systems will be expected to communicate with humans with ever increasing forms of emotional intelligence.

Other sensory modalities combined with vision and wearables will advance and most definitely expand the reach of AC powered systems in the next decade. Such highly innovative multi-sensory modalities truly offer the potential of taking AC out of the laboratory and into everyday scenarios, but many new problems and challenges will be encountered.

In preparation for these developments, there is still considerable multi-faceted research that must be conducted into psychology, physiology, and cognitive and computing sciences in order to further understand the emotional interplay between people, groups, authorities, objects and other sources of emotionally fuelled interactions.

Personalisation and customisation drivers already discussed in relation to vision and wearables also apply to other sensor modalities introduced throughout this section. As these additional affective sources (embedded in real-world settings) proliferate, the impact of environmental context and indeed the temporal aspects of emotions also need to be added into an already complex mix of human behaviour. This clearly outlines the requirements for computer scientists, psychologists, psychiatrists, medical professionals, brain researchers, linguists, speech professionals and other disciplines to objectively work together on the pursuit of multi-sensory enabled real-world AC systems.

Also on the horizon is the embedding of sensor modalities into the human body. For example, in relation to the complexity of the human brain and expected advances in EEG technologies, should technologies such as brain electrode implants and other sensory devices be embedded into the human body? While beyond the scope of this thesis, it is relevant at this juncture to consider if an individual should have the right to augment their body/brain with such implants and what procedures (medical, legal, ethical, social) need to be created and implemented to control such developments in the future.

The next section builds of the previous three AC modality related sections and investigates how multiple sources of affective data can be brought together into a multi-sensory fusion paradigm.

## 2.6 Affective Computing Multi-Sensory Fusion

The presented literature review indicates that the analysis and interpretation of affect is no longer just a single modality problem. In order to advance the AC field there is an ever increasing requirement for mixed modalities and applied sensory fusion based research to be carried out. Before starting this section, a general definition of data fusion is in order. Work by Khaleghi et al. (Khaleghi, Khamis, Karray, & Razavi, 2013) refer to a definition by the Joint Directors of Laboratories (White, 1991), [p. 28] who define data fusion as a *multilevel, multifaceted process handling the automatic detection, association, correlation, estimation, and combination of data and information from several sources*. This definition is a solid starting point and accurately sets out the focus for this section on the scientific and technological aspects of AC multi-sensory data fusion.

### 2.6.1 Affective Computing Multi-Sensory Fusion Scientific Aspects

Konar et al. (2015) describe multimodality (multi-sensory) as the *analysis of different manifestations of emotions* (Konar, Halder, & Chakraborty, 2015), [p. 12] which incorporates facial expressions, voice, brain signals, physiological data, body language and gestures. They point out that when experiments are conducted with different modalities on the same subject, the confusion matrices constructed for each individual modality have significant differences in terms of the percentage of emotion expressions correctly classified. According to Konar et al. (2015) these varying classification accuracies are an indicator that the *individual modality of classification is not highly reliable* (Konar, Halder, & Chakraborty, 2015), [p. 24]. To address this problem, the aim of multimodal fusion is the integration of individual modalities into a single representation of an emotion label with an increased probability value relating to the true emotion being felt and experienced by the subject.

In their work, Konar et al. (2015) present a review of a number of sensory fusion combinations that have been conducted in various applied research. These include (Konar, Halder, & Chakraborty, 2015), [p. 12 – 15]:

- *Audio + Visual:* (Fusion of facial and voice features).
- *Facial expression + Body gestures: (*Facial and body gestures of emotion).
- *Facial expression + Voice + Body gestures*.
- *Facial expression + Voice + Physiology.*
- *EEG + Facial expression.*
- *EEG + Physiology signals.*

Wagner et al. (Wagner, Lingenfelser, Andre, & Kim, 2011) explain two types of fusion techniques that are generally referenced in the literature.

- **Feature level (early) fusion:** All features from sensory modes are merged into a single high-dimensional feature set. A single classifier is then trained for emotion classification.
- **Decision level (late) fusion:** This involves the break-up of the feature set into subgroups to form an assembly of smaller classification models described by Wagner et al. (2011) as an ensemble. They explain how the term *decision-level fusion sums up a variety of methods designed in order to merge the decisions of ensemble members into one single ensemble decision* (Wagner, Lingenfelser, Andre, & Kim, 2011), [p. 212].

Vankayallapati et al. (Vankayallapati, Anne, & Kyamakya, 2011) also discuss multimodal fusion and explain some of the difficulties relating to feature level fusion. They argue that the feature sets produced from multiple modalities may be incompatible and also that the relationship and interaction between feature vectors from different modalities is quite an unknown field specifically from an AC perspective. In particular they highlight the following issues in relation to feature level fusion, *(i) the feature sets of multiple modalities may be incompatible (e.g., Eigen-coefficients of face and Mel-frequency cepstral coefficients (MFCCs) of voice); (ii) the relationship between the feature vectors of different biometric sensors may not be known; and (iii) concatenating two feature vectors may result in a feature vector with very large dimensionality* (Vankayallapati, Anne, & Kyamakya, 2011), [p. 3].

They discuss the curse of dimensionality (Vankayallapati, Anne, & Kyamakya, 2011) which is also a potential problem that can be expected to increase as further sensory modalities are engineered. Their multimodal research involves emotion recognition using decision level fusion of visual and acoustic features as represented in Figure 2-29 Decision Level Fusion. The diagram below demonstrates the approach taken with each sensor working independently in terms of acoustic and visual classification. The separate emotional classifications are then fed into a fusion classifier that produces an overall fused emotion classification result.

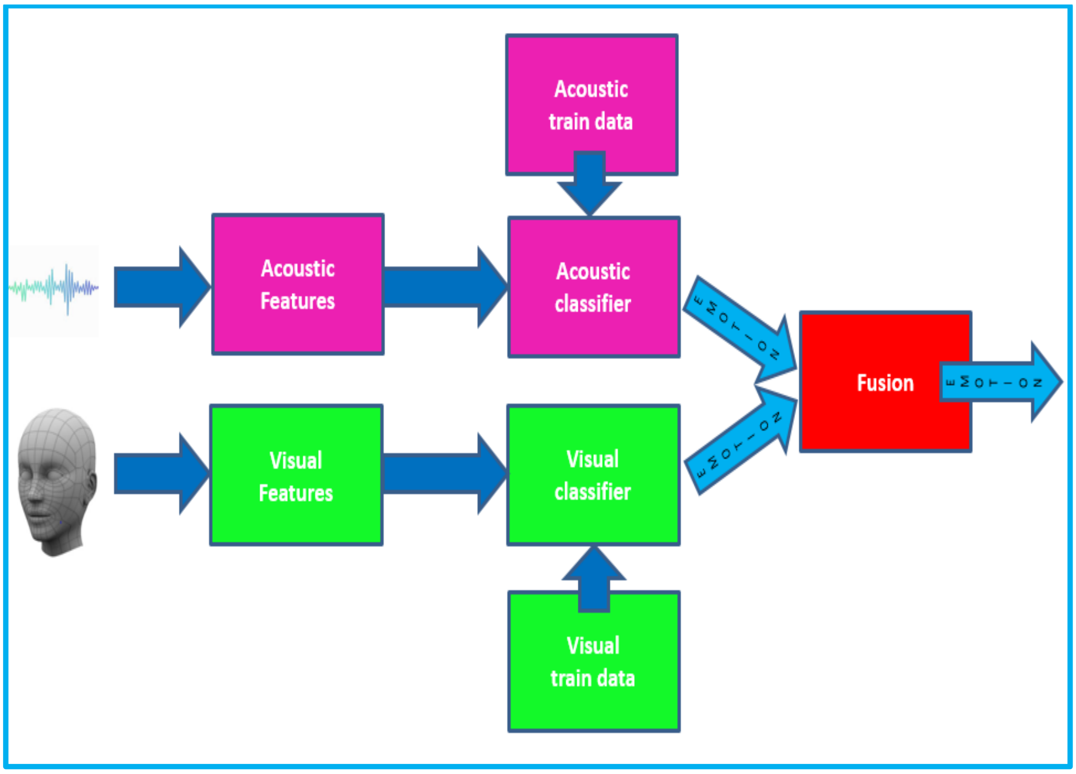



**Figure 2-29 Decision Level Fusion**

Wagner et al. (2011) also weight in positively on decision level fusion and its advantages over the use of a single classifier (Wagner, Lingenfelser, Andre, & Kim, 2011) as used in feature level fusion. In relation to training efficiency, a vast amount of data using a single classifier can be complex and inefficient. On the contrary, the partitioning of the data set for processing by independent sub-classifiers (ensemble) is more practical, time-saving and is also likely to be computationally more efficient. The authors discuss a divide and conquer approach when the dimensionality of one feature vector proves beyond the learning capabilities of a single classifier. Division of the feature space into *several (perhaps overlapping) distributions* (Wagner, Lingenfelser, Andre, & Kim, 2011), [p. 212] which are then handled by individual classifiers can address this problem according to the authors.

Wagner et al. (2011) argue the key tenet of their research in relation to missing data, which is a practical reality and challenge for multi-sensor fusion outside of the laboratory. Under a discussion on field performance, the point is made that dependence on a single classifier for multi-modal fusion in real-world settings is a high-risk strategy. Using an *assemblage of classifier models* (Wagner, Lingenfelser, Andre, & Kim, 2011), [p. 212] provides for situations where one classifier may be under performing but it can be supported by the ensemble when such cases arise. Wagner et al. (2011) further state that a decision level fusion approach facilitates the engineering for situations in relation to sensor failure, noise, occlusion, power outage, etc. The affective reasoning capabilities of such a system could also produce an estimate or best guess using past performance statistics from a sensor's data sets in order to deal with any missing data.

A number of decision level fusion techniques and how they handle missing data are discussed in (Wagner, Lingenfelser, Andre, & Kim, 2011). These techniques are an important part of the AC decision making process at a fusion level. They mathematically enable and facilitate the processing of ensemble member decisions in order to create a single overall ensemble decision. Algebraic computation of combinations of classifier outputs, ranking methods, voting schemes and various weighting methods are examples of strategies used in decision making from multi-sensor data fusion. Techniques such as weighted majority voting, weighted average, sum rule, mean rule, product rule and arousal-valence cross-axis combination are described along with details of how the algorithms can cope with missing data from an ensemble member. Explanations of these techniques are outside the scope of this review but can be referenced in (Wagner, Lingenfelser, Andre, & Kim, 2011), [p. 212 – 214]

Work already discussed by Lefter et al. (Lefter, Burghouts, & Rothkrantz, 2016) involving both speech and gesture modalities is revisited here from a sensory fusion perspective. As a reminder, their research investigated the distinction between stress conveyed by the intended semantic message (the spoken words for speech and symbolic meaning for gestures made) and stress conveyed by the modulation of speech (intonation) and gestures (speed and rhythm). The work investigated both the semantics (what is being communicated) and modulation (how the message is being communicated) aspects of the communication signals.

Acoustic features, speech transcriptions (words) and video features were extracted to form the low level feature set. The low level features represented in diagram Figure 2-30 Stress Recognition - Low and Intermediate Level Features were then processed whereby acoustic features were analysed by a speech modulation module to detect how the sound of speech represented stress levels. The speech transcription words were analysed for evidence of arousal and valence from a stress perspective and the words were also analysed according to stress related topics. The video features were extracted and analysed for gesture modulation (extent and manner of gesture made), arousal, and valence and by topic classification from sixty established gestures that indicate stress.

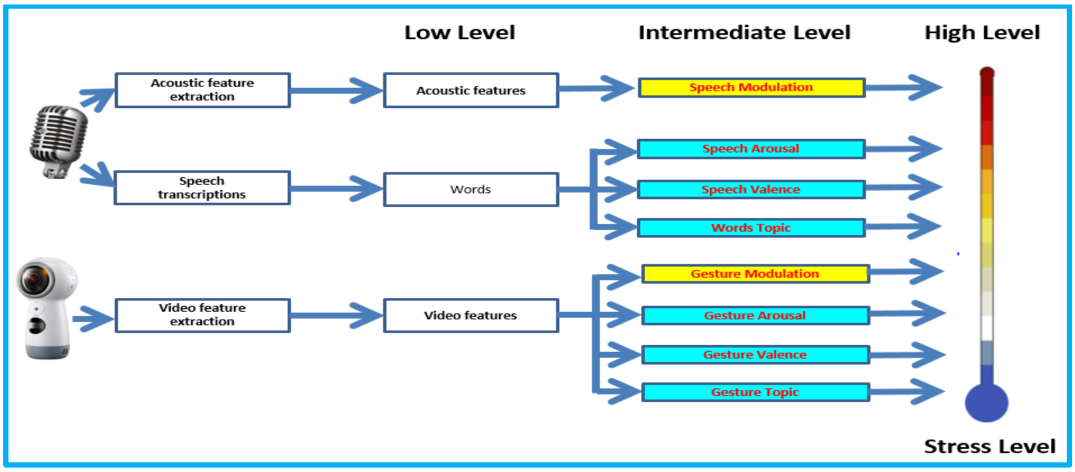



**Figure 2-30 Stress Recognition - Low and Intermediate Level Features**

The findings emphasise that stress is conveyed by a large variety of combinations of both speech and gestural actions. Just relying on the speech without the gesture combination could lead to the loss of micro expressions of stress or wrong interpretations of a scenario. They also found that gesture frequency increases as stress levels increase and that the use of the intermediate level variables *significantly improves over the baseline of predicting stress from low level audio-visual features* (Lefter, Burghouts, & Rothkrantz, 2016), [p. 174] alone.

This work of Lefter et al. (2016) also indicates a number of central issues relating to this specific research thesis and hardens the fact that sensory fusion techniques can infuse increased levels of confidence in the affective analytical process. The research conducted by Lefter et al. (Lefter, Burghouts, & Rothkrantz, 2016) significantly highlights that the very process of fusion based research is leading to new findings about sensory and human emotion interactions. In their work, this was specifically in the form of the creation of an intermediate feature layer created from the low level speech and video based gestures for stress monitoring and identification.

The Emotion and Pain Project (Emotion & Pain Project, 2017) uses the fusion of multi-view high resolution facial videos, head mounted and room audio signals, full body 3D motion capture and electromyography back muscle signals. A representation of the sensor set-up is reproduced in Figure 2-31 EmoPain Sensor Configuration. The project and the related EmoPain datasets aim to open up new thinking, research and groundwork for the development of affective sensitive systems for chronic lower back pain (CLBP) (Deyo & et al., 2014). Aung et al. (Aung, et al., 2016) use eight high resolution cameras (five frontal subject views), two long range and a floor camera to capture downward facing facial expressions. Audio recording are captured via two channels on a central camera with full subject view and also on a second head mounted camera.

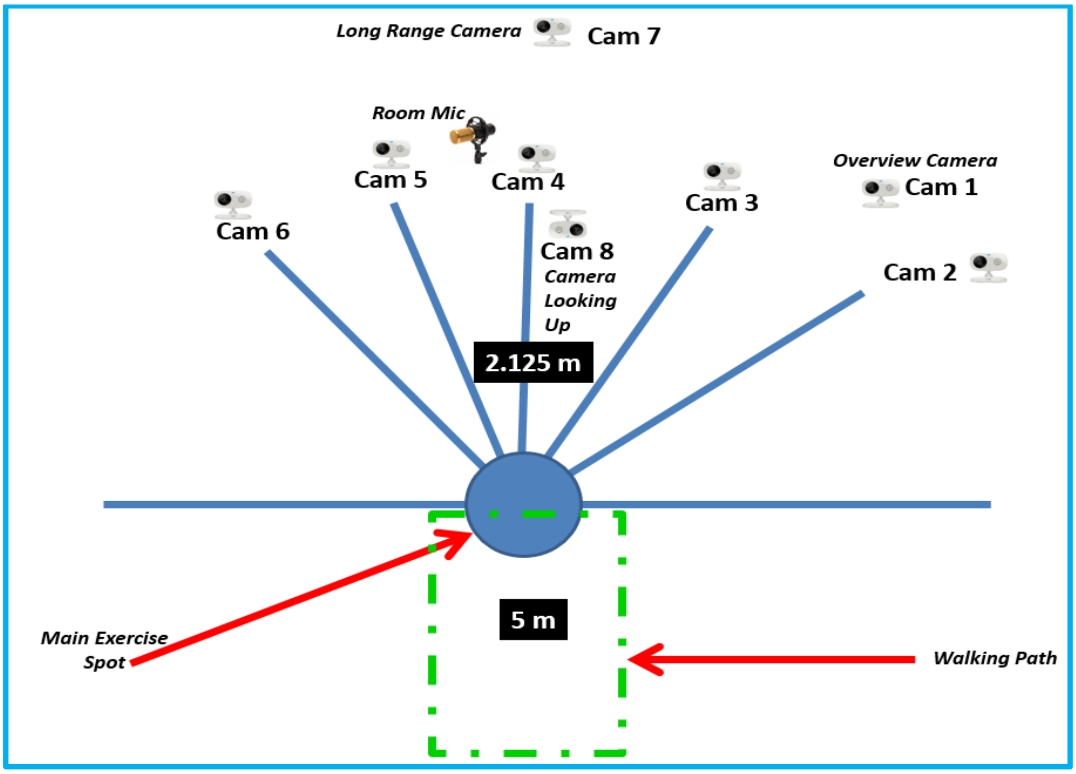



**Figure 2-31 EmoPain Sensor Configuration**

A customised motion capture suit the Animzaoo IGS-190 (Meta Motion, 2017) was used along with four fully wireless surface BTS FREEEMG 300 (BTS BioEngineering, 2017) electromyography sensors.

The EmoPain datasets contain data streams from a number of affective data sensory sources (video, audio, gait/body, EMG). In relation to the processing of the facial and body movement data feature sets, a key finding is that there seems to be a *low concurrence between facial pain expressions and guarding/stiffness (which is a category used in relation to body behaviour)* (Aung, et al., 2016), [p. 15]. Aung et al. (2016) discuss *preliminary experimentations to investigate the possibility of automatically recognising the facial expression of pain and pain related body movement behaviours* and have provided related accuracy results in section 6.1 and 6.2 (Aung, et al., 2016), [p. 11 - 12]. The authors suggest that face and body expression of chronic pain may indeed occur separately and that care must be taken when fusion of these modalities are being considered and especially in the case of CLBP.

The Emotion and Pain project is an excellent example of multiple sensors focused on a single applied health related problem with true global reach. Here again, the very process of fusing the sensory data is providing new quantitative data, knowledge and insights into emotion and pain expressions and also how temporal factors come into play in relation to emotion display or its suppression.

Monkaresi et al. (Monkaresi, Bosch, A. Calvo, & D'Mello, 2017) discuss how engagement in learning is considered in four stages, namely, engagement beginning; sustained attention or engagement; disengagement (attention fades) and re-engagement. In experiments, students completed an academic writing task and provided engagement annotations concurrently as they completed the task and retrospectively from their facial videos taken during the task.

This work used three sources of sensory data that resulted in the fusion of (1) geometric facial features (FT) extracted using the Kinect Face Tracking SDK

(Microsoft, 2017), (2) facial appearance features extracted using local binary patterns in three orthogonal planes (LBP-TOP) (Monkaresi & Hussain, 2012) and (3) PPG technology for the video based sensing of heart rate (HR). The Figure 2-32 Feature and Decision Level Fusion demonstrates how the authors created two feature-level fusion models (Feature3 and Feature2) and two decision level fusion models (Decision3 and Decision2) which were created from the classification outputs from the original feature models (FT, LBP-TOP and HR).

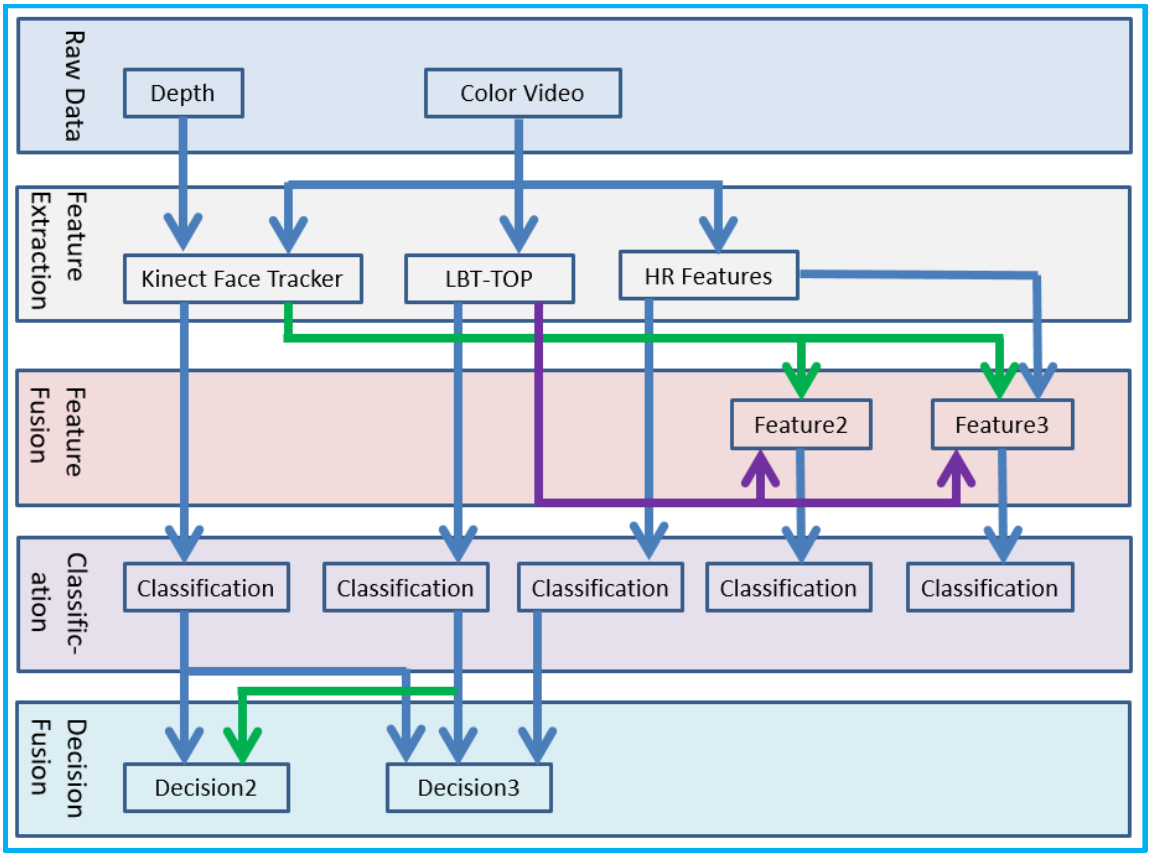



**Figure 2-32 Feature and Decision Level Fusion**

The research highlighted the current limitation in remote video based heart rate measurement but that future improvement can be expected in such remote sensory technologies. Findings clearly positioned facial expression analysis (FT and LBP-TOP) as higher performing in terms of classification accuracy. Also noted is that the fusing of channels resulted in noticeable performance improvements over the best individual channel which was FT. Monkaresi et al.

(2017) state that *fusing the individual FT and LBP-TOP models across both fusion schemes (feature and decision levels) yielded more accurate results over fusing all three channels (presumably due to the lower performance of the HR model)* (Monkaresi, Bosch, A. Calvo, & D'Mello, 2017), [p. 23]. As demonstrated in the Figure 2-33 Concurrent and Retrospective Results, for this engagement related research, feature-level fusion outperformed decision-level fusion, and the most accurate model was the Feature2 model (i.e. FT + LBP-TOP), with the concurrent area under the curve (AUC) (Google, 2018) percentage as 0.758 and the retrospective AUC percentage as 0.733.

| | Concurrent – AUC % | Retrospective – AUC % |
|---|---|---|
| HR | 0.544 | 0.590 |
| FT | 0.635 | 0.666 |
| LBP-TOP | 0.645 | 0.664 |
| Feature 3 | 0.751 | 0.697 |
| Feature 2 | **0.758** | **0.733** |
| Decision 3 | 0.635 | 0.683 |
| Decision 2 | 0.690 | **0.730** |

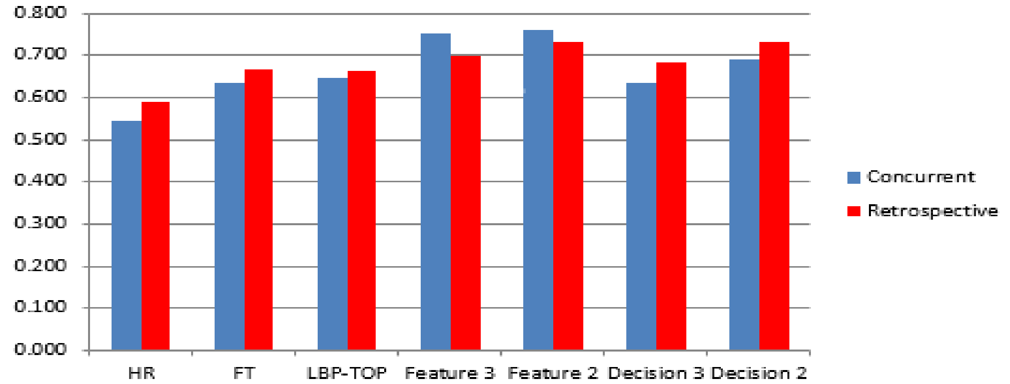



**Figure 2-33 Concurrent and Retrospective Results**

**Sensory Fusion Architecture:** The work of Dasarathy (Dasarathy, 1997) presents a multimodal fusion architecture that specifies the typical inputs and outputs of a multi-sensory system. This architecture has application across many fields in engineering and science and is presented here as a formal scientific basis relating to design considerations for affective sensory fusion systems.

Dasarathy (1997) describes a number of fusion processes which are discussed below and that are summarised in Table 2-2 Sensory Fusion Approaches.

| **Fusion Approach** | **Description** |
|---|---|
| Data In - Data Out (DAI-DAO) | Defined sensor data inputs produce defined data outputs. |
| Data In - Feature Out (DAI-FEO) | Fusing of sensor data inputs to create feature output. |
| Feature In - Feature Out (FEI-FEO) | Fusion is now based on pre-processed data and no longer on direct sensor outputs. |
| Feature In - Decision Out (FEI – DEO) | Features are analysed to make a decision. |
| Decision In - Decision Out (DEI-DEO) | Fusion of multiple decisions that have been derived from processed features, to derive a higher level decision. |

**Table 2-2 Sensory Fusion Approaches**

**1) Data In–Data Out (DAI-DAO) Fusion:** This involves the fusion of data inputs to create fused data outputs. According to Dasarathy (1997), this type of fusion is commonly referred to as data fusion and is applicable to the extraction of detail in the data that may otherwise be lost without the fusion process at the data level.

**2) Data In–Feature Out (DAI-FEO) Fusion:** In this fusion mode, data inputs are fused in order to produce some form of feature in relation to the phenomenon under observation. Dasarathy (1997) provides two examples of this type of fusion. The first example relates to how visual information data inputs from both human eyes are used to produce the feature of depth perception. Dasarathy (1997) explains how the computation of an object's surface temperature may be produced by using the *intensities from two infrared (IR) bands of a multispectral scanner* (Dasarathy, 1997), [p. 28] as another example of data in - feature out mode of fusion processing.

**3) Feature In–Feature Out (FEI-FEO) Fusion:** In this fusion processing mode both the inputs and outputs are features and this mode is primarily referred to as feature fusion in the literature. In this scenario, each sensor may have its own unique set of data structures. To explain this Dasarathy's describes how *shape features obtainable from an imaging sensor may not be available from a nonimaging radar and on the other hand, range information obtainable from the latter may be outside the scope of the former* (Dasarathy, 1997), [p. 28]. These two sets of feature data from both the imaging and radar sensors can then be fused together in order to produce the volumetric size of a target that is being tracked by the sensory fusion system which is a typical fusion activity at the feature level.

**4) Feature In–Decision Out (FEI-DEO) Fusion:** In this fusion mode the inputs are features from different sensors and the fusion process produces a decision as output. Dasarathy (1997) explains that this method of fusion is associated with pattern recognition systems involving multi-sensor inputs in the recognition phase where the *feature vector (consisting of feature information from different sensors) is classified on the basis of a priori knowledge and/or training, to arrive at a class label (decision)* (Dasarathy, 1997), [p. 29].

**5) Decision In–Decision Out (DEI-DEO) Fusion:** This mode is generally referred to as decision fusion in the literature with both the inputs and outputs of the process being decisions.

Dasarathy (1997) describes his initial fusion taxonomy as being limited to the above five main modes but which can be viewed as *building blocks of more complex fusion system architectures*, (Dasarathy, 1997), [p. 29] which he discusses in further detail in his research.

The following presents a number of key observations reproduced from Dasarathy's research, (Dasarathy, 1997), [p. 29] in relation to the five sensor fusion processes discussed above.

- DEI-DEO fusion is more robust and better resistant to individual sensor failures than other levels of fusion.
- DAI-DAO fusion and DAI-FEO fusion are highly sensitive to factors such as the specific nature of the individual sensors, how they replicate or complement one another.
- DAI-FEO (Data/feature) fusion is also susceptible to individual sensor failures.
- DEI-DEO fusion is most tolerant to individual sensor subsystem failures.
- The FEI-DEO fusion scenario represents a decision structure that could derive reasonably good decisions with only a partial feature set but with much less reliability than one that uses the entire feature set.
- The computational complexity of having a very large feature set is one of the disadvantages of fusion in the FEI-DEO mode.
- The computational demands of the DEI-DEO mode is generally much less than under other modes.

- Sensor alignment is an essential part of the DAI-DAO and DAI-FEO fusion processes and is generally thought of as the pre-processing phase to the fusion process.

Dasarathy presented a flexible fusion architecture which is reproduced from his paper in Figure 2-34 Dasarathy's Flexible Architecture for Fusion Potential Exploitation. With reference to his flexible fusion architecture, Dasarathy (1997) advises that for optimal fusion system design, all of the five fusion processing modes need to be fully explored and exploited in order to take advantage of the maximum information available from within and across the sensor network. He also acknowledges that factors such as the types of sensors and indeed the sensor suite configuration may deem some of the fusion processes impractical from a fusion architecture perspective.

Dasarathy (1997) visualises that his flexible fusion architecture can provide for a *mix of inputs at different levels; for example, features from some sensors and decisions from same or other sensors as input to a fusion process whose output is at the decision level. Similarly, a mix of data and feature inputs to a fusion process with features as output can also be possible under some scenarios* (Dasarathy, 1997), [p. 30].

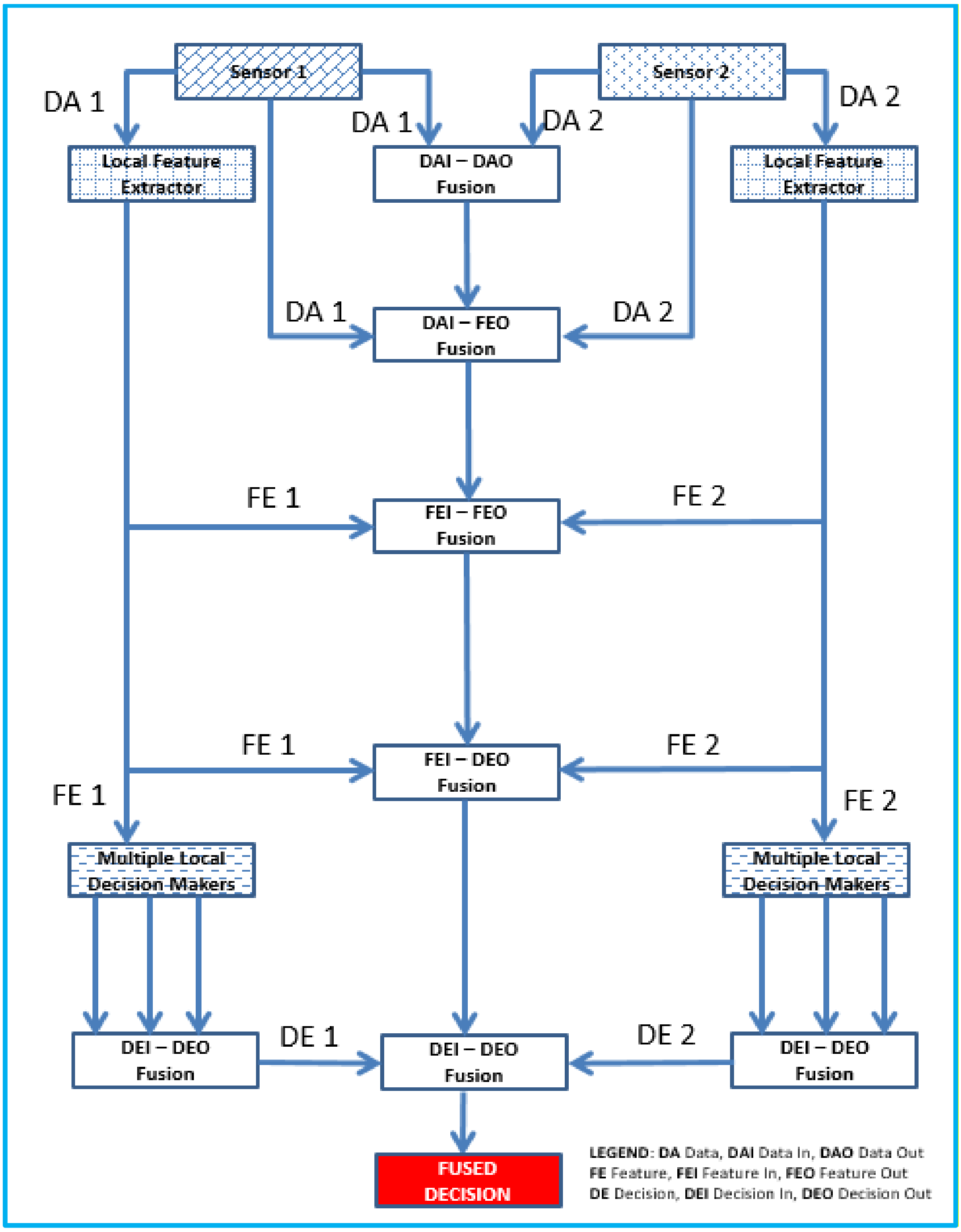



**Figure 2-34 Dasarathy's Flexible Architecture for Fusion Potential Exploitation (Dasarathy, 1997)**

Dasarathy's (1997) fusion architecture is highly significant and directly relates to the thought processes, conceptualisation, modelling and engineering work that was conducted as part of the overall thesis research. The fusion architecture is of particular relevance to the next chapter on information modelling and the conceptual architecture of a prototypical AC system.

Following the above insights into the theoretical and scientific aspects of multi-sensory fusion, the next section presents a discussion on technologies that are applicable to AC sensory fusion research.

### 2.6.2 Affective Computing Multi-Sensory Fusion Technologies

Schmidt et al. (Schmidt, Decke, & Rasshofer, 2016) used subjective driver state measures, and psychophysiological and vehicular data in simulated driving scenarios in which emotional and cognitive states were measured. The study used the iMotions (iMotions, 2017) human behaviour sensing research platform which is a fusion of affective related hardware and software technologies from a range of providers. One interesting conclusion to their research was that heart rate variability and skin conductance levels were found to be strong indicators of the driver's state but that they are very much driver-dependent. Schmidt et al. suggest that to *benefit from these strong correlations in future driver state detection, self-learning systems will be required that can adjust the signal weighting for each driver* (Schmidt, Decke, & Rasshofer, 2016), [p. 1385]. Table 2-3 iMotions Sensing Technologies presents a selection of sensor technologies that are integrated into the iMotions research platform.

iMotions is a research platform designed to enable researchers to concentrate on the specifics of their study rather than dealing with the complexities of interfacing across multiple sensors. The platform has major academic and corporate clients and is referenced across the scientific literature (iMotions, 2017).

The platform was used for an interesting multi-sensor research project that was aimed at determining *whether driving while talking hands free is really less dangerous than talking while holding a cell phone* (iMotions, 2015). This research involving the Center for Automotive Research at Stanford University (CARS)

(Stanford University, 2017) used both facial expression analysis and eye tracking services from the iMotions software. The Figure 2-35 CARS and iMotions Research provides an overview of the set-up involved during the driving simulation exercises conducted.

| **Affective Technologies** | **Manufacturers** |
|---|---|
| Eye tracking | Tobii (Tobii Group, 2017), EyeTech (EyeTech Digital Systems, Inc., 2017) |
| Mobile eye tracking | Glass (Google, 2017) type devices Tobii |
| EEG headsets | Emotiv (Emotiv, 2017), Advanced Brain Monitoring (ABM) (Advanced Brain Monitoring, Inc, 2017) |
| GSR, ECG, EMG & Respiration Sensors | Empatica (Empatica, 2017), Shimmer (Shimmer, 2017) , BioPac (BIOPAC, 2017) |
| Facial expression analysis | Affectiva (Affectiva, 2017), Emotient (Emotient, 2017) |

**Table 2-3 iMotions Sensing Technologies**

A key finding of the research from the sensory analytics in relation to the eye tracking data *suggests that while both groups kept their eyes on the road, the hands free group scanned the road significantly more than the handheld group* (iMotions, 2015). This case study demonstrates the use of a dedicated sensory fusion platform and its potential for increasing productivity in AC and AS research activities.

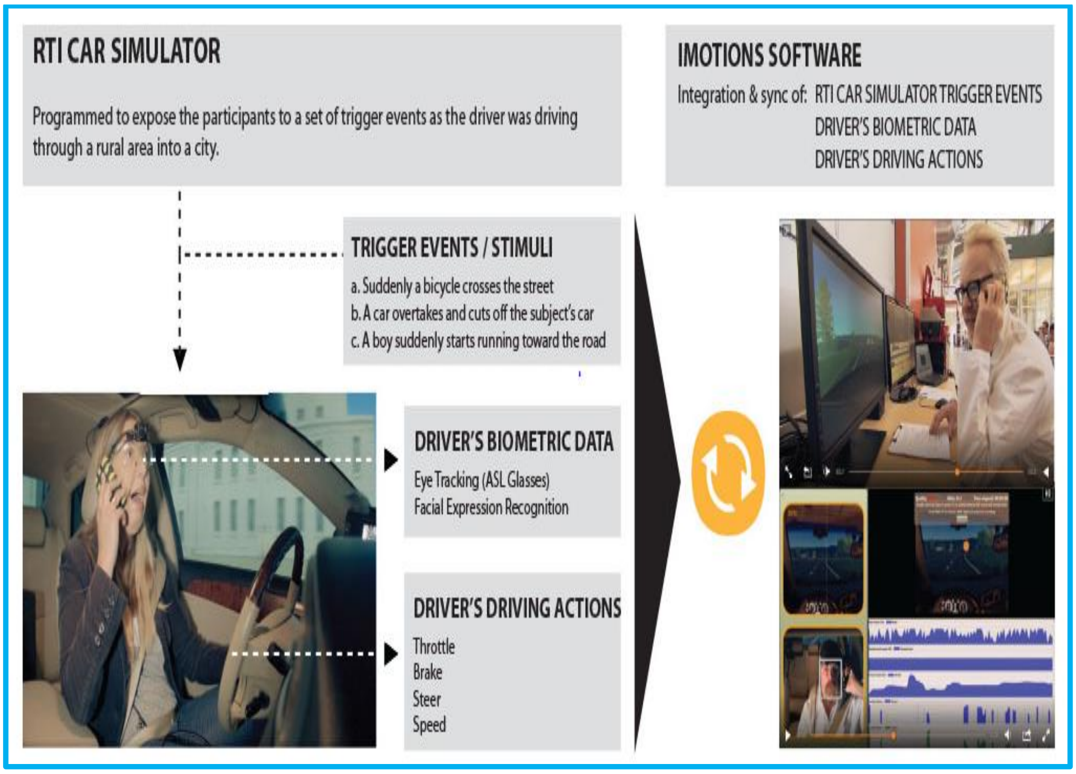



**Figure 2-35 CARS and iMotions Research (iMotions, 2015)**

From the research conducted, the iMotions platform stands out as both an academic and commercially established research fusion platform. Other providers can certainly be expected in the future and indeed vertical sector related (eHealth) fusion platforms are also likely to be developed.

The final concluding part to this section provides additional theoretical insights into the complex problem that is sensory fusion, and discusses the many problems and challenges that AC researchers are expected to encounter in the future.

### 2.6.3 Discussion on Remaining Problems and Challenges

Khaleghi et al. (Khaleghi, Khamis, Karray, & Razavi, 2013) produced a SoTA review paper and present a number of the problems and challenges facing the multi-sensory data fusion paradigm. Their work relates to many disparate fields where data fusion occurs but a number of the challenges and problems they discuss are also extremely relevant to AC fusion based research.

Khaleghi et al. (2013) explain why data fusion is such a challenging task and advise that *the majority of issues arise from 1) the data to be fused, 2) imperfection and diversity of the sensor technologies, and 3) the nature of the application environment* (Khaleghi, Khamis, Karray, & Razavi, 2013), [p. 29].

Khaleghi et al. (2013) present a number of problems and challenges that impact on any typical data fusion process. A selection of these are summarised below.

**Data imperfection:** Sensor data will always be affected by some level of impreciseness as well as uncertainty in the measurements.

**Outliers and spurious data:** This is a factor of impreciseness and noise in the sensor measurements. This can also be caused by ambiguities and inconsistencies present in the environment.

**Conflicting data:** Special care is required in the handling of conflicting data.

**Data modality:** Data fusion may be required from similar modalities such as multiple types of vision cameras or from different multi-sensor modalities as in the case of AC involving vision, audio, text, speech, gait, and eye tracking for example.

**Data correlation:** Data fusion algorithms must also take into account any possible bias influences on sensor data (noise) as this may lead to over/under confidence in the results.

**Data alignment/registration:** This challenge relates to the correct alignment, registration and calibration of sensors for the data acquisition task. This involves accounting for any calibration errors that may be induced by individual sensors and it also needs to consider environmental parameters and related local and global knowledge. Khaleghi et al. (2013) advise that *data registration is of critical importance to the successful deployment of fusion systems in practice* (Khaleghi, Khamis, Karray, & Razavi, 2013), [p. 29].

**Data association:** This relates to the association of sensor data with specific targets in a typical multi-target tracking environment.

**Processing framework:** The data fusion process may be performed in a centralised or decentralised design framework.

**Operational timing:** Related challenges include environmental aspects of sensor placement; operational frequency of similar sensors may vary; sensor timing variations; with distributed fusion out-of-sequence arrival of data has to be handled. All of these timing factors can impact on the overall fusion performance.

**Static vs. dynamic phenomena:** Relates to sensory data that may be time-invariant or varying with time. Khaleghi et al. (2013) advise that *data freshness i.e. how quickly data sources capture changes and update accordingly, plays a vital role in the validity of fusion results* (Khaleghi, Khamis, Karray, & Razavi, 2013), [p. 29].

**Data dimensionality:** This issue may be addressed by the pre-processing of sensor data locally at the sensor nodes or globally at a fusion node where data compression may be intelligently applied before further onwards processing in the fusion network. Factors to consider are bandwidth savings; power usage; and minimising computational loads specifically in the central fusion node.

Khaleghi et al. (2013) believe that, to the best of their knowledge there is no single fusion algorithm capable of addressing all the above outlined problems and challenges.

Their work presents a review of a number of multi-sensor data fusion algorithms that individually aim to address a subset of the problems and challenges discussed. Their work has led to the creation of a taxonomy which represents the many types of fusion algorithms under the four thematic areas of 1) fusion of imperfect data, 2) fusion of correlated data, 3) fusion of inconsistent data and 4) fusion of disparate data. See Figure 2-36 Multi-sensor Data Fusion Algorithms Taxonomy based on (Khaleghi, Khamis, Karray, & Razavi, 2013), [p. 30].

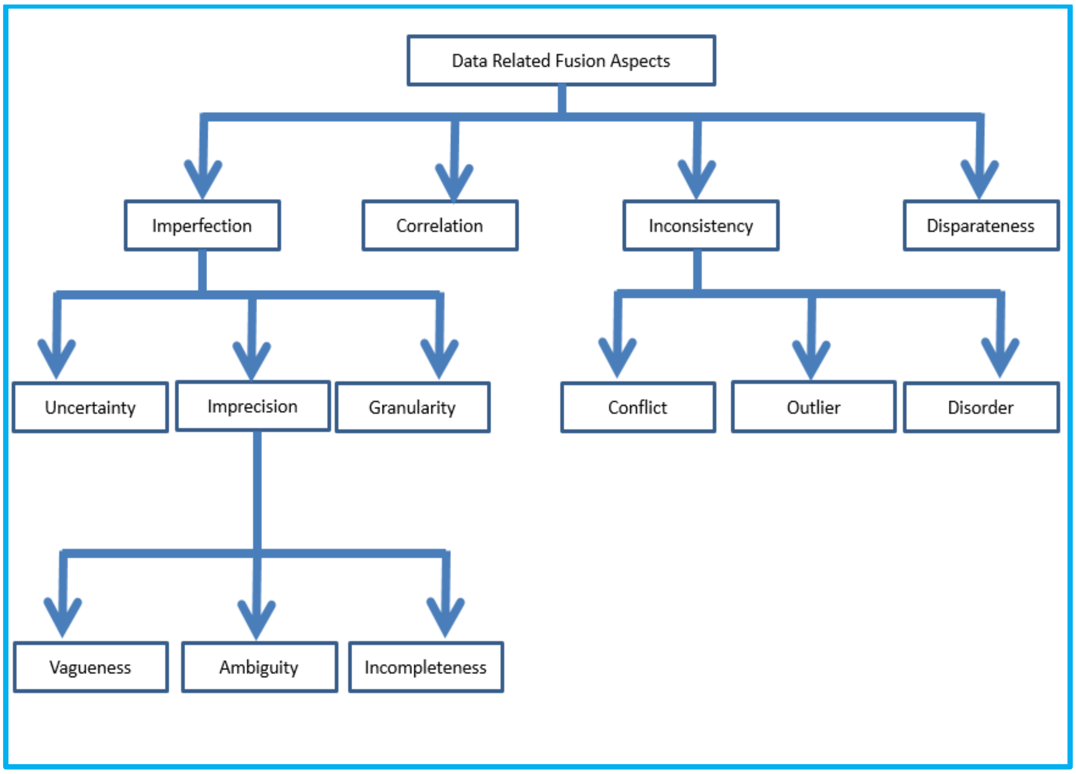



**Figure 2-36 Multi-sensor Data Fusion Algorithms Taxonomy**

Detailed discussions on the algorithms described by Khaleghi et al. (2013) are outside the scope of this research but some of their concluding points and remarks are relevant from an AC fusion perspective.

Hard data is typically from calibrated electronic sensory sources, whereas soft data is described as human-based data *expressed preferably in unconstrained natural language* (Khaleghi, Khamis, Karray, & Razavi, 2013), [p. 38]. According to Khaleghi et al. (2013) this trend is leading to fusion frameworks for hard and soft data fusion that account for both human and non-human sensory data. In AC sensory fusion, this is certainly the case where there are hard data based electronic sensors but also there is the processing of facial images, physiological signals, speech, sentiment, gait, gestures, EEG signals and other sources, that are all data observations generated from the human body via signal, language and many other forms.

Other opportunities and challenges were discussed in relation to adapting and learning within the fusion network for situational environments where key parameters may not be known in advance or in situations where there may be temporal and dynamically changing environmental states.

Khaleghi et al. (2013) also discuss topics such as automated fusion where adaptable algorithms could be created using *machine-automated prototyping* (Khaleghi, Khamis, Karray, & Razavi, 2013), [p. 39] techniques. They discuss belief reliability and the concept of uncertainty about uncertainty and also highlight security fusion (data integrity, confidentiality and freshness) which certainly must be a mandatory integrated component of any form of cloud based, decentralised, centralised or hybrid fusion schemes in the future.

To wrap up this section on sensory fusion, in the future there may possibly be two or more layers of affect abstraction. Affective intelligence will exist at the sensory layer and this will see devices with more on-board embedded affective algorithms and processing capabilities. These sensory modalities will then communicate their affective states to a sensory fusion layer, typically deploying the types of classification and fusion decision algorithms discussed by Khaleghi et al. (2013).

At this higher level fusion layer, applied intermediate features will be computed depending on the specific AC application domain in question. Further processing incorporating personalisation, fusion security, adaptability, learning, fine-tuning and other layers may also be developed to increase the sensitivity and specificity of real-time emotion classification fusion processing.

The objective of this section was to provide an introduction to the multi-sensory data fusion paradigm and to relate the theoretical and scientific aspects of the problem to AC research directions. Having studied the many forms of AC sensors, this section aimed to tie it all together and to highlight the complexities and challenges in creating AC powered multi-sensory fusion platforms/services for real-world cognitive based applications.

## 2.7 Affective Computing Related Research Activities

This section provides a review of three EU research projects that are interrelated with the thesis research that has been conducted. An architectural conceptual model relating to how AC could be integrated into a typical multi-user GBL environment, a demonstrator of AC integrated with psychotherapy/counselling virtual agent based service and further details on the SenseCare eHealth platform are presented across three sections. Also included is a related research section that outlines the work of established research institutions and network organisations working in the AC and AS fields.

### 2.7.1 S-Cube Games Based Learning (GBL) Project

AC was theoretically investigated as a potential means of advancing the 3D virtual world GBL S-Cube (Asperges, et al., 2014) platform which was an EU RISE project in entrepreneurial skills training for the social enterprise sector. This section provides an overview of the project and specifically the potential for AC integration into S-Cube and game based platforms in general.

**S-Cube overview:** S-Cube is a European Commission (EC) funded Leonardo Da Vinci Transfer of Innovation project titled Using Online Role Play to Promote Soft Skills Development for Social Enterprises. The S-Cube project represents the collaboration of four transnational EU education and training providers; Plymouth University (UK); Cork Institute of Technology (Ireland); University of Naples (Italy) and GeProS (Germany). The name S-Cube represents the three S's associated with the project which is **S**oft **S**kills for **S**ocial Enterprises.

Social enterprises are mainly established by civil society or third sector organisations and groupings (Nyssens & Kerlin, 2005). They include a wide array of initiatives focused on such areas as childcare, employment programmes for the unemployed, care for elderly people, and social information provision.

The S-Cube project involved the development of an e-learning tool to support the improvement of soft skills for social enterprises and was completed during the period January 2012 to December 2013. The overall mission of the S-Cube project was to spread the use of online learning (through open source provision) as a way of providing a training experience to enhance the soft skills of individuals working within social enterprise settings.

**S-Cube GBL platform:** The S-Cube 3D online software platform includes features for trainers and players. The trainer controls allow for the creation of offline and online multiplayer games; intervening during games and management of debriefing sessions. The features for players allow them to participate in multiplayer games and in trainer led debriefing sessions. A typical multi-player interactive scenario is depicted below in Figure 2-37 S-Cube Multi-Player GBL Platform.

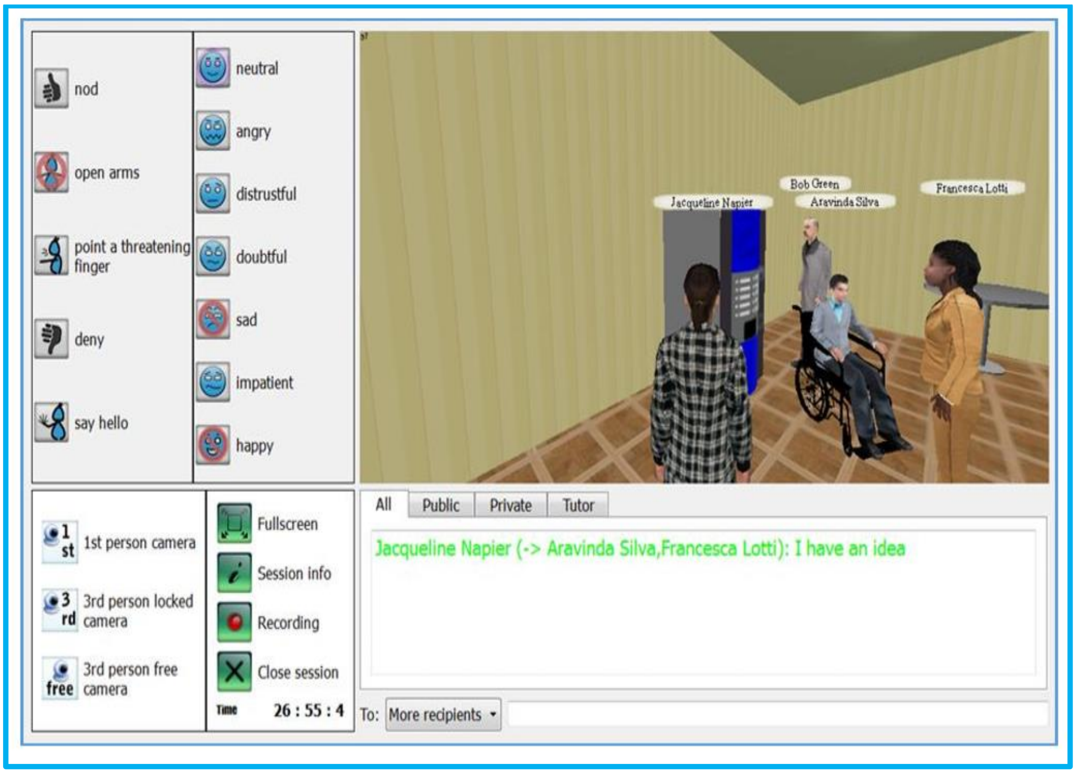



**Figure 2-37 S-Cube Multi-Player GBL Platform**

The S-Cube GBL platform was developed using EUTOPIA which is a development platform that originated from a previous project called (SISINE) (Miglino, Di Ferdinando, Rega, & Beninca, 2007). The EUTOPIA platform incorporated Irrlicht (IrrLicht, 2016) an open source real-time 3D engine written in C++, RakNet (Oculus, 2017), a network API designed for games development and Qt (Qt, 2017), C++ class libraries and developer tools.

**Role of affective computing in S-Cube:** From a player emotional interaction perspective, messages can be associated with one of seven emotional expressions for role playing characters. This involves the selection of an icon on the player panel to indicate neutral; angry; distrustful; doubtful; sad; impatient or happy. Avatars can also make a certain number of gestures such as opening their arms, agreeing, disagreeing, finger pointing and saying hello during a game.

The S-Cube interface is primarily via mouse and keyboard. From an affective and perceptive capability, changing body language, communicating emotional feelings and verbally interacting all at the same time is not technically possible in the current iteration of the platform. While there are many technical options to enhance the S-Cube such as speech to text, machine translation, text analytics, and video integration, parallel research was conducted during the project into how affective computing could be integrated into game based platforms such as S-Cube.

This work incorporated research and development in vision using early versions of the Real Sense SDK and investigations also considered how an affective software analytics engine could convey emotional state information to players and trainers in games based (including GBL) software environments. The overall outcome of the early stage S-Cube AC related research was to present an architecture model that demonstrated how GBL platforms such as S-Cube could be re-engineered and complimented with affective capabilities. In the case of S-Cube, an affective architecture model was created and titled Affective **C**omputing **T**hrough Sens**O**ry **R**ecognition (ACTOR) and is depicted below in Figure 2-38 S-Cube - ACTOR Architecture Overview.

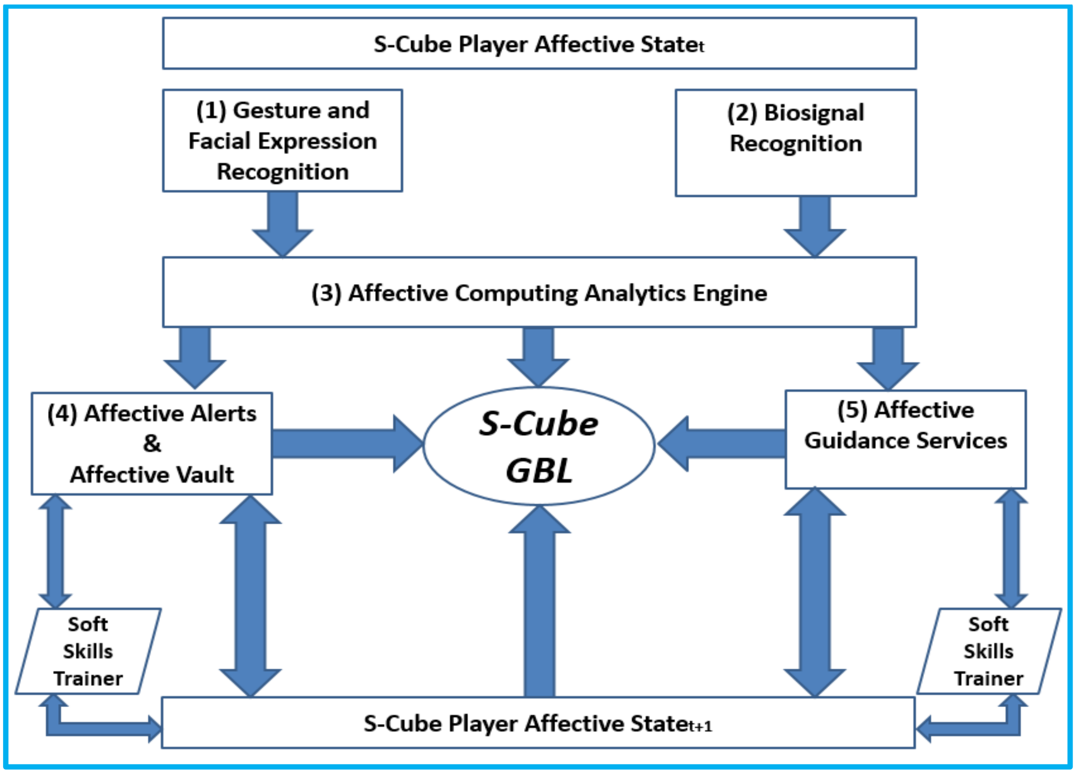



**Figure 2-38 S-Cube - ACTOR Architecture Overview**

S-Cube ACTOR uses vision (1) and physiological inputs (2) that are processed by an AC analytics engine (3) which is responsible for the fusion and prediction of a player's emotional states. The affective alerts and vault (4) service is specifically focused around the S-Cube game but it also has generic application. Alerts could be aimed at players or trainers/supervisors while the vault of affective states may be used for post-learning evaluation or for the analysis of how a person's affective states change during longer term training programmes (and thus contributing to personalisation). This secured retrospective aspect of ACTOR can also provide for the development of personalised affective models of player behaviours thus optimising overall platform performance. The affective guidance services (5) are designed to assist a player with recall of past scenarios of emotion behaviour and could also be used to provide real-time communication tips and assistance during emotionally charged events they are experiencing.

The ACTOR proposal was a proof of concept research and was not formally part of the S-Cube project, but from research conducted during the trials of the non-affective version of S-Cube there were clear player preferences for a more intuitive platform (Keary, et al., 2016). As referenced previously there is increasing evidence of awareness and action by the games sector in relation to the potential that AC architectures, models and technologies could being to both the leisure and learning games industry. ACTOR was presented at GBL and other conferences (Keary & Walsh, 2014), (Keary & Walsh, 2014), (Keary & Walsh, 2013), (Keary, Walsh, O'Byrne, Moizer, & Lean, 2013) as a vision of how a GBL platform could be affectively enabled. Today with the many advances in the AC field, the ACTOR architecture has true potential to be developed as a multi-function suite of AC services for GBL and other types of games platforms.

Through S-Cube, collaborative relationships were developed with the Italian partners Università degli Studi di Napoli Federico II (UNINA) (UNINA, 2017). This then led to new research into how AC could be integrated into a project called ENACT (ENACT Consortium, 2015), which is discussed next.

### 2.7.2 ENACT Psychological Game and Analytics Project

The ENACT game is the product of the European funded ENACT (**E**nhancing **N**egotiation Skills Through On-Line **A**ssessment of **C**ompetencies and Inter-active Mobile **T**raining) (ENACT Consortium, 2015) project. This section provides a brief overview of the ENACT project and also discusses a prototype system that was developed as a demonstrator of the potential of AC integration into a virtual agent platform.

**ENACT overview:** The game is organised into independent scenarios where the user plays different characters and has to communicate and negotiate with various virtual agents in real and everyday life situations. ENACT incorporates an internal psychological negotiation model which is based on the five styles of handling interpersonal conflict proposed by Rahim (Rahim, 1983). This model used by occupational psychologists differentiates five styles based upon two basic dimensions of concern for self and concern for others.

Considering that ENACT incorporated aspects of psychological counselling in relation to inter-personal communications it was considered a good candidate for AC research. In conjunction with one of the ENACT project partners, University of Naples, it was agreed to investigate how AC technology could be integrated and a prototype demonstrator was to be developed by SIGMA researchers.

**Affective computing potentials in ENACT:** In the existing ENACT platform, mood is selected by the player from a number of mood icons presented on the screen. It was decided to integrate the Real Sense vision based emotion tracking classes with the Unity 3D games development engine to perform automatic tracking of the human player's face in real-time.

A scoring algorithm was applied to evaluate the likelihood of a specific emotion being felt by the user when communicating with the virtual agent. The resulting prototype replaced the screen based user select mood button with a vision based emotion analytics component integrated via Unity 3D. The evaluated emotion is now shown in a message box (which changes colour to reflect the emotion) along with the Rahim based system generated communication choices that are made available for the user.

The screen capture in Figure 2-39 ENACT Game with Vision Based AC Integration demonstrates the game in action with the player appearing on camera underneath the ENACT virtual agent. Anger is identified as the emotional mood of the player; this is marked on the top of the screen with the Rahim answer back suggestions on the left hand side which may be typical of an Anger fuelled response from the player back to the virtual agent.

**Other ENACT related research:** The AC enabled ENACT prototype proof of concept system was exclusively tested at SIGMA. In conjunction with the University of Naples the prototype was presented along with a poster at the Brain Informatics and Health - 8th International Conference, (BIH) 2015 held in London (Keary, et al., 2015). The presentation titled *Seriously Intelligent Communications Skills Mentor* was selected to indicate both the affective, psychological and computationally intelligent potential that is becoming available for the development of serious mentoring and counselling systems for domains where human consultation is not available, highly-sensitive or indeed too costly.

This prototype also acts as an example of how AC could be integrated with online self-help/training systems that provide psychotherapy and counselling services.

Following the ENACT proof of concept project work, the thesis research focused exclusively on the future potential of AC across the eHealth domain. This focus incorporated AC research into stress management, QS, agitation tracking, dementia and Alzheimer's care. SenseCare is a major AC eHealth project that has originated out of this PhD research thesis and further details are presented in the next section.

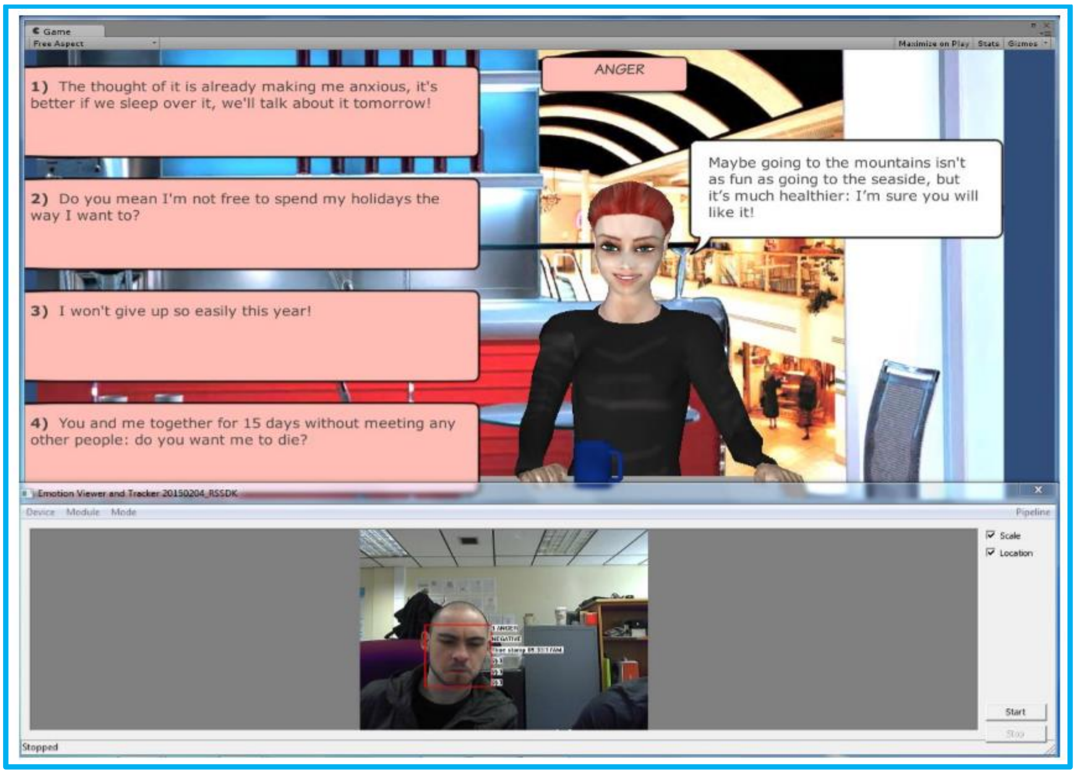



**Figure 2-39 ENACT Game with Vision Based AC Integration**

### 2.7.3 SenseCare eHealth Dementia Care Project

This section provides further details on the SenseCare EU research project.

**SenseCare overview:** The SenseCare project solution aims to integrate data streams from multiple sensory sources and to fuse these streams to provide a global assessment that includes objective levels of emotional insight, well-being and cognitive state of a subject (monitored person). The potential exists to integrate this holistic assessment data into multiple innovative applications across connected healthcare and various other inter-related and independent domains. SenseCare is thematically aligned with the current EU Horizon 2020 themes of *Internet of Things* (European Commission, 2014), *Connected Health* (European Commission, 2013), *Robotics* (European Commission, 2014) and the *Human Brain Project* (European Commission, 2015).

A general non-technical overview of SenseCare is presented in Figure 2-40 SenseCare Overview.

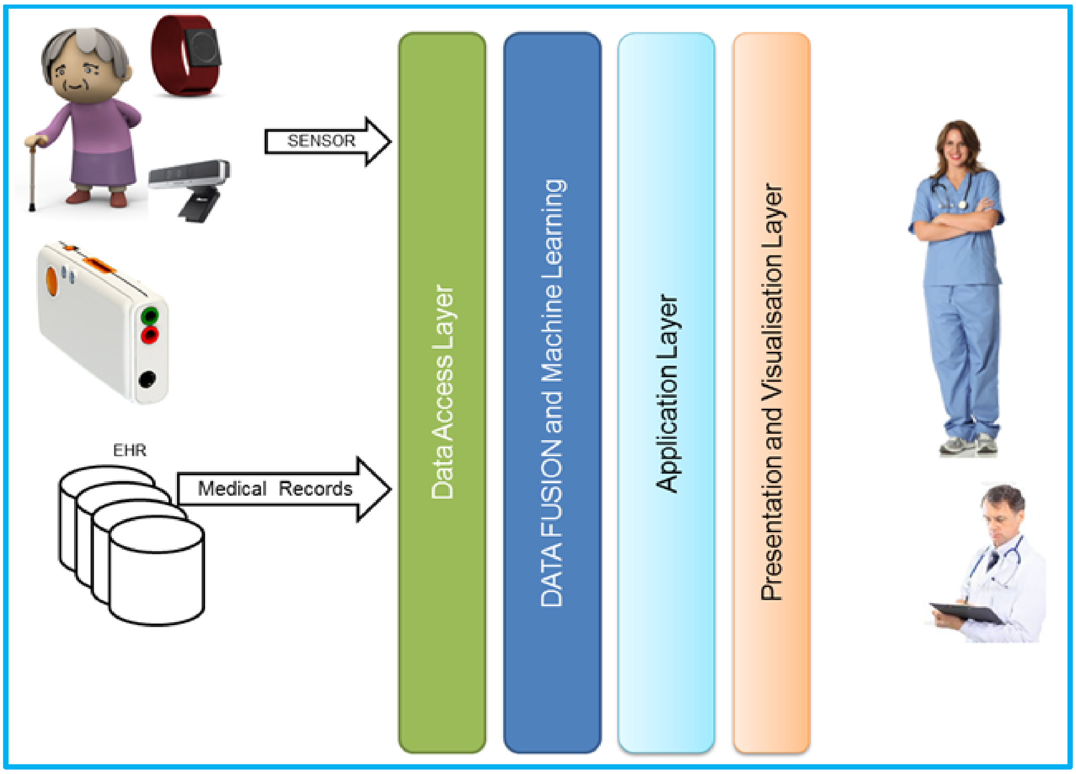



**Figure 2-40 SenseCare Overview**

The eHealth potential and justification has already been presented in chapter one so the focus of this section is more on the technical aspects of the platform and the various work packages involved in the project.

**SenseCare technical overview:** The SenseCare project has set out the following defined objectives:

- Development of the SenseCare affective computing powered platform as an extensible multi-layered architecture based on open standards.
- Develop, test and deploy various prototype software modules in the SenseCare software platform.
- Specify and enforce security, legal and ethical guidelines in relation to the deployment and use of SenseCare powered applications in the healthcare field.
- Implement selected use cases as test pilots for the dementia care and connected health domain using the SenseCare platform.

- Trial, test and evaluate feedback on the above test pilots with patients, care givers and healthcare professionals.

To address these objectives, the project partners have taken responsibility for a number of the technically related work packages (WP).

**WP1 Use Case Requirements**: This work package will identify, define and specify the most relevant use cases in which the SenseCare platform will ultimately be deployed. Use cases in dementia care and eHealth will be identified and defined with particular focus and attention to where emotion state data will best be used to support patients, healthcare professionals (doctors, psychiatrists, psychologists, care workers) and caregivers (on-site-facility and in the home).

**WP2 Affective Computing and Machine Learning:** This WP will develop and apply affective computing algorithms to form the intelligent nucleus of the SenseCare platform. New innovative algorithms and techniques will be invented and applied alongside established technologies from the field(s). Statistical and machine learning algorithms will also be deployed for integration with the data fusion and medical informatics application layers of SenseCare.

**WP3 Big Data Fusion and Machine Learning:** This WP will develop a number of input interfaces for specific sensory devices such as cameras, wearables and Internet of Things. Consortium partner expertise in cloud services, embedded systems, multi-stream data fusion and machine learning will be applied throughout this work package in order to deliver the sensory interface and data fusion layers of the SenseCare affective computing platform.

**WP4 Psychology of AC**: This work package will apply the most current thinking, models and algorithms from psychology and will form an integral input to other work packages. Along with the generic nature of psychology, specific research and development will be carried out into the psychological aspects of dementia care and connected health for patients, professionals and care givers. This work will also form vital inputs to WP1 (Use Case Requirements) and WP2 (Affective Computing and Machine Learning).

**WP5 Medical Informatics:** This work package is responsible for the configuration, interface, deployment and testing of the use case SenseCare applications that have been specified in WP1 (Use Case Requirements). SenseCare powered test pilot applications will be deployed with access to cloud based affective state data to provide a range of services to the dementia and connected healthcare domains. A key deliverable of this module will be the full testing, validation and reporting on the use case software applications.

**SenseCare architecture:** SenseCare is primarily composed of a four layer software architecture (see Figure 2-41 SenseCare Four Layer Architecture) that will be engineered and developed across the WPs described above.

- ***Application Layer:*** This layer provides for the deployment of the use cases developed in WP1 and engineered by WP5 as a set of dementia care related medical informatics apps.
- ***Services Layer:*** This layer incorporates a range of development activities across WP2, WP3 and WP4. Affective computing, machine learning, sensory fusion, semantic and metadata processing and ontology management takes place here with processing and functionality at both lower and higher levels in the architecture. Low level activities are generally in relation to raw sensory processing and affective analytics. Higher order processing is where the semantic and ontological models of

dementia care are applied for interfacing with the application layer. The services layer also provides underlying functionality for quality assurance and data filtering services that will evolve throughout the life of the SenseCare platform. These services will provide for lower level sensory data management and also can be expected to provide higher level quality assurance and monitoring services that may be customised on a more personal level in relation to a person with dementia (PwD). Big data services (Hadoop Ecosystem), a workflow engine (Apache Hue) and a *Person Data Life Cycle Management* system (engineered and developed by consortium partner FTK (Kowohl, et al., 2016)) will form part of the underlying architecture infrastructure of the SenseCare services layer.

- ***Resources Layer:*** This lower level layer of the platform is responsible for the processing of data received by AC based sensors that have been deployed for a PwD. This layer incorporates a number of resource adaptors for the processing of affective signal data from video, wearables, audio and other sources.
- ***Infrastructure Layer:*** The SenseCare platform will make use of storage and compute cloud services in the final deployment of the project platform.

SenseCare is an exemplary, highly ambitious proof of concept project relating to affective computing and sensory data fusion. The project will produce a wealth of research publications, knowledge, findings, and AC related expertise throughout its duration. The multi-sensory and fusion aspects will be of most significance, as will the applied eHealth related use cases which will ultimately supply invaluable insights into the actual uptake of AC powered eHealth systems by end users in typical real-world settings.

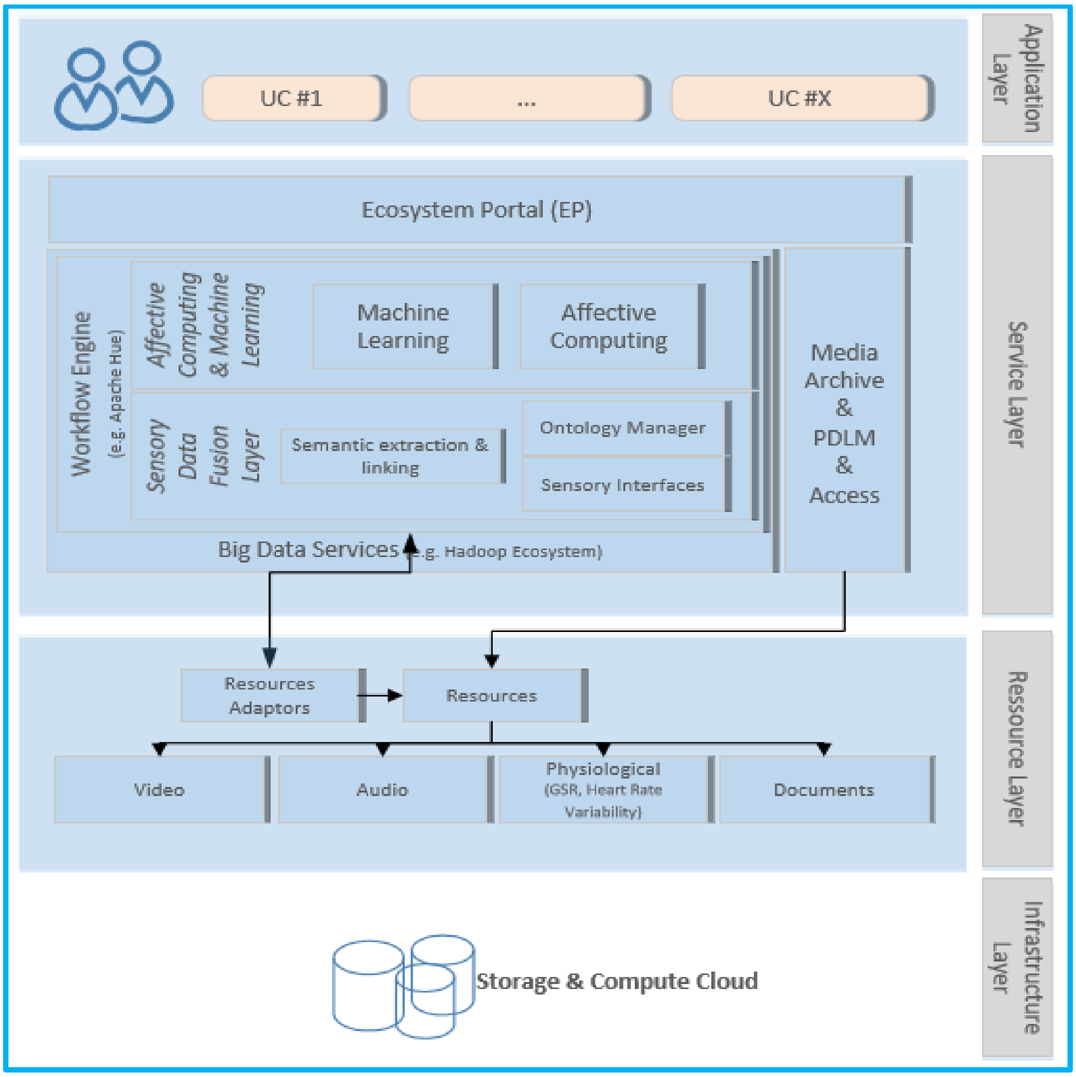



**Figure 2-41 SenseCare Four Layer Architecture**

This research thesis has been a major influence in relation to the origins and on-going development of the SenseCare project but any further detailed discussions are outside the scope of this section.

### 2.7.4 Other Affective Computing Related Research

The Affective Computing Research Group at the Massachusetts Institute of Technology (MIT), Media Laboratory (Massachusetts Institute of Technology (MIT), 2017) is one of the most influential research teams in the world. This group works across many aspects of AC with notable research projects since 1997. The group has a solid focus on the practical (out-of-laboratory) wearable sensory signal processing and machine learning aspects of AC. Projects conducted by the MIT group are strong in vision, wearables, and sensory fusion aspects and also tend to have a medical and quantified self-focus.

MIT research projects have already been discussed in this chapter. The footnote link below provides details on current AC projects being conducted by the MIT group[9]. Some of the more relevant projects described by MIT are briefly outlined below with further details available at the footnote link address.

**Objective Assessment of Depression and its Improvement:** Using wearable sensors and smartphones the project monitors physiological data, voice, sleep patterns and social interactions. It aims to provide early diagnosis, prevention and assessments of depression.

**Wavelet-Based Motion Artifact Removal for Electrodermal Activity:** This research provides for the removal of motion artifacts from EDA data streams.

**Real-Time Assessment of Suicidal Thoughts and Behaviours**: Using wearable devices and smartphones this research aims to identify behavioural, affective, and physiological predictors of suicidal thoughts and behaviours.

**EDA Explorer:** This project uses a highly accurate machine learning algorithm which can automatically detect noise within the data. It can also detect skin conductance responses, which are spikes in the signal indicating a fight or flight response in an individual.

**Onsite Stress Measurement:** Using AI and AC the project aims to advance the measurement, understanding, and management of stress in real-life settings.

[9] https://www.media.mit.edu/groups/affective-computing/overview/

The Swiss Centre for Affective Sciences (Swiss Centre for Affective Sciences, 2017) conducts emotion research into the analysis of verbal and non-verbal affective behaviour, and physiological and brain region activity measurements. The centre has a mixed discipline focus and attracts researchers from multiple fields such as computer science, linguistics, neuroscience, biology, history, law, economics, medicine, psychology and philosophy.

While MIT is focused mainly on AC (with some AS related research) the Swiss centre is strongly focused on AS research with AC as an integrated element of various research projects. The footnote link below provides a description of current AS/AC research projects conducted at the Swiss centre[10]. The following is an extract and brief overview of five selected project, with full details available at the footnote link address.

**From Elicitation to Emotional Response: Neural Mechanisms of Patterning and System Synchronization:** This project researches the nature and patterning of the responses in different components of emotion, the interrelations between emotional components and emotion regulation.

**Emotional Future Thinking:** This research investigates the cognitive processes through which emotion influences episodic future thoughts.

**Power and Emotion Recognition Accuracy:** The main goal of this project is to investigate the relationship between interpersonal power (i.e., the extent to which a person is able or willing to influence or control others) and emotion recognition accuracy (i.e., the ability to assess correctly the emotions of others).

---

[10] https://www.affective-sciences.org/home/research/projects-and-foci/research-projects/

**Emotion, Attention and Value:** This research investigates the links between affective traits and attention, the links between attention theory and emotion theory, and the impact of the emotion-attention connection on value theory.

**Adaptative Emotion Awareness Tools for Computer-Mediated INTeractions (EATMINT):** The EATMINT project relates to emotional awareness across collaborating entities. EATMINT aims to assess whether the knowledge of the emotional state of an attendee in a communication/collaboration process actually informs the outcome. If so, such emotional knowledge could then be used to guide an attendee with a sense or understanding of the emotions of another person with language and a more relevant communication strategy being adapted accordingly.

The Association for the Advancement of Affective Computing (AAAC) emerged out of the Humaine (AAAC, 2004) EU FP6 (EU, 2015) Network of Excellence project. AAAC acts as a global hub for researchers from academia and commercial organisations involved in research on affective computing, emotions and human-machine interaction. The site has established a number of special interest groups (Entertainment; Ethics; Patents; Personality, and Speech) and provides access to a catalogue of various tools which include emotion description; experimental methods; signal analysis, and emotion classification (AAAC, 2015).

The objective of this section was to present an overview of other thesis related research that has been conducted, and that has driven the initial investigatory and preparatory work that has advanced the thesis research and its hypothesis evaluation processes. MIT and the Swiss Centre for Affective Sciences provided a global leader's perspective while the AAAC introduced a developing global network of researchers, professionals, and services for the AC and AS community.

## 2.8 Summary and Scope of Remaining Thesis Research

This chapter opened with a general introduction to the field of AC. This was followed by a section on psychology and AC which presented and explained the link between AC and AS. This section also provided insights into various theories, methods, tools and techniques from psychology that are relevant to AC research.

The next three sections of chapter two concentrated on the sensor technologies that have contributed to and that have led to current advances in AC. The first of the sensor sections studied the scientific and technological aspects of computer vision and the major role it has played in advancing the AC field. This was then followed with a dedicated section on wearables which are increasing in importance and relevance to the understanding of the interplay between emotional responses and physiological signals. The third section compiled a selection of other hardware and software based forms of sensor modalities used in AC research today. It investigated voice, EEG, computers inputs (keyboard, mouse, touch) and gait as other input methods of affective data along with sources such as raw text and sentiment analytical techniques.

The section on sensory fusion discussed in the research directly relates to the multi-sensory fusion problem, which is at the very core of AC. This section highlighted the importance of scientific and technological data fusion methods and the critical role they are playing in current AC research.

Each of these four sections also provided a summary that addressed the many remaining problems and challenges that exist in the AC field. These sensor and fusion related problems and challenges will be summarised in the form of an audit and will be revisited in the closing chapter six of the thesis where further related updates, findings, and issues will be investigated and discussed in relation to the futures of AC.

Chapter two also provided a section on other related research which aimed to provide the reader with an overview of relevant and practical projects, activities and outcomes related to the thesis research conducted.

**Scope of remaining thesis research:** The state of the art research has provided essential groundwork and insight into the justification, direction and preparatory work required in order to pursue and evaluate the thesis research hypothesis. In particular, it has investigated the role of psychology and has helped identify the complex nature of emotional processing in AC systems. It has also provided insights into various tools and techniques available for conducting the AC experiments for this thesis.

The research investigations across all of the current and emerging AC sensor modalities and their related science and technologies has clearly identified that sensitivity and specificity (i.e. predictive performance) is one of the most critical aspects of AC research, and that improvements and innovations in relation to emotion recognition accuracy is paramount and must be a continual research focus in order to advance the futures of the AC field.

Throughout the research for this chapter, it has also clearly emerged that AC is no longer unimodal based and has become a major multi-sensor, multi-fusion problem that is augmented by the work being conducted in the general field of sensor data fusion.  Multi-sensory fusion is a central theme of this thesis and in conducting the state of the art research it was also realised that while there are a range of bespoke software infrastructures in academic circles, no formal conceptual architecture that could advance and grow across the field of AC was generally available to researchers.

In consideration of the above discussion on the justifications and core outcomes of this state of the art research the Table 2-4 Thesis Objectives and SoTA Sections provides a review of the first five thesis objectives and how they have been addressed by the research and investigation work conducted for chapter two.

| Thesis objective | SoTA related sections |
|---|---|
| TO1 Investigate the role of psychology in AC research: | Section 2.2 |
| TO2 Investigate the scientific aspects of AC literature and research activities: | Sections 2.1 to 2.7 |
| T03 Investigate the range of hardware and software technologies used in AC research: | Sections 2.2 to 2.6 |
| TO4 Conduct research into relevant future AC application domains: | Sections 2.3 to 2.7 |
| TO5 Research the use of data fusion techniques in current AC multi-modality research: | Section 2.6 |

**Table 2-4 Thesis Objectives and SoTA Sections**

As a means of directing the reader through the remainder of this thesis, a short overview of chapters three, four and five which address a number of the remaining thesis research questions and objectives are outlined below.

**Chapter three - Conceptual Modelling and Design:** Chapter three presents further details on functional application domain use cases and the information modelling and data stream components of the AC research infrastructure artifacts that were developed as part of the research activities. The multi-sensory fusion aspects of both vision and wearables along with a conceptual architecture presenting both the current and further potential of a suite of prototypical software artifacts developed during the research is also provided.

**Chapter four - Proof of Concept and Implementation:** Chapter four presents lower level details on the tools and base technologies that were used throughout the research. Further technical software and hardware details on the engineering and development of the specific technical components and services incorporated into the AC infrastructure prototypical solution artifacts suite are presented throughout this chapter.

**Chapter five - Evaluation:** Chapter five incorporates the evaluation of the research thesis hypothesis via AC experimentation methods and techniques. Details are provided on the conceptualisation, formalisation, set-up, running, dataset pre-processing, statistical techniques, data reporting and analytics, evaluation, and overall research findings/conclusions relating to the AC experiments that were conducted.

That concludes the AC state of the art scientific and technological research investigations chapter of this thesis. The various research activities conducted this far and the learning/knowledge garnered from the various research phases have certainly contributed towards the formulation and creation of a conceptual model and design architecture of a prototypical AC platform which is now proposed and discussed in the next chapter of the thesis.

# 3 Conceptual Modelling and Design

The main focus for this chapter is on the modelling and design aspects of a conceptualised multi-sensory fusion AC platform. Considering chapter one and chapter two, the research orientation has primarily navigated toward the application of AC with an eHealth propensity. With this in mind, the first section of chapter three presents related use cases of AC in an eHealth setting. This is then followed by a high-level discussion on the functional and non-functional requirements of a proposed AC platform.

Following this, section two introduces an established data stream information model that has originated from the domain of multimedia. This multimedia stratification model is used as foundation to create two unique AC stratification models that are relevant to single and multi-sensory fusion. While the discussion in this section is at a conceptual level of information modelling it also provides a drill down into two specific AC modalities (vision and wearables) and presents sensor and feature related explanations of typical data streams.

The third section revisits sensory fusion as discussed in chapter two and applies the first of the AC stratification models to present a practical framework primarily relating to individual sensory processing functionality. Section four discusses and applies the second AC stratification model to an overall architecture for a multi-sensory fusion platform. This section provides details and a conceptualised insight into the multi-layered architecture and discusses the types of services required for dealing with the complexities of delivering affective intelligence in a multi-sensory environment. Section five presents an overall summary of chapter three for the reader.

### 3.1 Use Case Descriptions and Requirements

This section presents a description of a number of applied use cases that specifically relate to the main motivation and navigation of this research towards the eHealth domain (including stress and quantified self) already discussed across chapters one and two. This is then followed with a review of the functional and non-functional requirements of a conceptual AC platform with specific reference to vision and wearable sensor integration.

#### 3.1.1 Use Case Descriptions (eHealth Focus)

The discussion around the use cases below presents a narrowing down of the scope of this research from the initial broader aspects discussed in chapter one to a set of applied use cases. The use cases explained below typically relate to a general eHealth context and are all potential candidate application solutions for the conceptual AC platform architecture described throughout this chapter.

- **Note:** In the context of the following use case descriptions, User1 refers to the person/subject that is being tracked by the AC platform.

**Use case #1: AC monitoring of personal communications**

User1 is living alone and is being monitored by an AC platform. User1 receives regular phone calls from connected family members and friends. The family members or a care giver regularly monitors the emotional well-being of User1. The AC platform sends a communication alert in relation to an observed decline in the emotional well-being of User1.

More detailed analytics reveals that the decline may be due to the loss of a phone call communication with a particular family member on a regular basis. This then leads to the family member in question being contacted and asked to ensure they keep up more regular contact with User1. Since this regular communication was reinstated, current analytics reports on User1 show a marked improvement in their emotional wellbeing.

**Use case #1 translation potential:** This use case applies in many social interaction scenarios. It is relevant to social media monitoring, care and support of the elderly, security monitoring and many other application scenarios where emotional and well-being state changes may be impacted by human communication processes.

**Use case #2: AC monitoring of everyday object interactions**

User1 lives on their own and enjoys watching TV, listening to music and also video recordings of his wife and children from past family events. User1 has a multi-media entertainment system but has recently begun to experience difficulty in the turning on and selection of their preferred media activity.

User1's apartment is fitted with an AC platform for the monitoring of emotional well-being. As User1 interacts with the multi-media system, the AC platform detects increasing levels of stress, frustration, anger and disgust. On reaching certain pre-defined emotion levels, the platform actively advises via text message a reminder to User1 of how to access the required content on the multi-media system in a simple set of step by step instructions.

The AC platform then stores the affective analytics for the episode for further processing and deeper insights into the stress and frustration that was caused at the time. Such insights can assist family members and carers in improving or eliminating objects that are likely to cause further stress and frustration for User1 in their home.

**Use case #2 translation potential:** This use case applies to persons interacting with everyday objects and can also apply to technology interface points. Wherever there are scenarios where excessive stress, frustration and anger is generated from object interactions then there may be possibilities for AC powered interventions and support. Such timely interventions can offer business, legal, insurance, ethical, societal, medical and many other benefits to citizens in the future.

**Use case #3: AC monitoring and analytics for well-being**

User1 has been experiencing mood-swings that have started to have serious impact on both work and home life. Under direction from a medical professional, User1 has agreed to be monitored by an AC platform while at work and at home. The AC platform started gathering affective data on User1 over a two week period using vision and wearable sensors.

After two weeks, quantifiable affective data on User1's well-being was presented to the medical professional. The evidence suggested specific time periods where excessive levels of stress, aggression, and anger may have existed for User1.

In a formal review with the medical professional, two pressure points were identified for User1. One pressure point was in relation to a bi-weekly work management meeting. The second pressure point happened the morning before the work meeting at home and also on returning home after the meeting.

In consultation with all involved parties, a work intervention and related actions were carried out. This led to a resolution of the main pressure points with a better quality of work/home life balance for User1.

**Use case #3 translation potential:** This use case relates back to the previous discussions on psychoneuroimmunology (Newman, 2016), (Keary & Walsh, 2014) and the medical impact of stress on the human body. This can relate to all forms of human to human, human to computer, human to technology and human to navigation/control system interactions. AC systems offer the potential to identify pressure points, recommend interventions and also provide qualified support and assistance.

**Use case #4: AC monitoring in medical/rehabilitation care facilities**

Due to a traumatic accident User1 has an acquired brain injury. After rehabilitation efforts User1 is still left with extremely limited communication skills and thus unable to express himself correctly. Family members are concerned about his mental health and emotional well-being.

An AC platform has been installed at User1's rehabilitation care facility. The emotion analytics from the platform have identified varying levels of positive and negative emotional states with a worrying degree of excessive negative periods. Deeper analysis clearly identifies emotional negative dips when there is a staff changeover to night staff. Also during the day shifts, similar emotional dips were identified during group sessions for patients. This was due to User1 being mixed in with an Alzheimer's group which was totally unacceptable for his age profile.

The affective based evidence has led to specific interventions and a full reassessment of the care plan and the needs of User1. Ongoing monitoring via the AC platform has ensured that care needs are fully met by the care facility staff and management and it has also made a significant contribution to User1's improved rehabilitation as well as providing detailed insights on emotion well-being for family members.

**Use case #4 translation potential:** As humans live longer, their emotional support and monitoring both in their home and in care facilities is vital to ensure their dignity, quality of life and that medical services are maintained to a consistently professional standard. AC systems and platforms have the potential to assist the elderly, their family members and can also act as a source of alternative insights to assist medical professionals with care, medical, diet, exercise and medication plans.

The four use cases outlined above present scenarios for a typical person (User1) that has accepted to be monitored by an AC platform. The use cases presented very much relate to the eventuality of the technologies being accepted into everyday environments (eHealth in relation to the above use cases). User1 in the above use case scenarios represents the person under affective analytics throughout their daily activities and can generally be seen as the producer/source of the affective data processed and created by an AC platform.

There are also consumers of the AC outputs from the platform and with reference to the eHealth domain these may be medical professionals, AC researchers/developers, eHealth data scientists, healthcare workers, family members and naturally the producer (User1) may also be a consumer of the platform generated affective data outputs. For completion purposes, a number of use case scenarios are envisioned and outlined below from an AC consumer perspective.

**Medical professionals use case scenarios:** The following use case scenarios are envisioned for medical professional users of an AC platform.

- AC sensory configuration requests for clients.

- AC video analytics on clients.
- AC physiological analytics on clients.
- Drug treatment correlation analytics with client AC analytics.
- AC clinical reporting on client moods (recently, daily, weekly).
- AC reporting for other medical professionals, healthcare workers and family members.
- Technical feedback loop to AC researchers and eHealth data scientists.

**AC researchers/developers use case scenarios:** The following use case scenarios are envisioned for AC researchers/developers of an AC platform.

- Building platform based anonymised data sets.
- Testing and developing AC algorithms on the platform.
- Integration, testing and fusion of new AC sensor hardware and software.
- Developments of innovative AC use case applications.
- Technical feedback loop to medical professionals and eHealth data scientists.

**EHealth data scientists use case scenarios:** The following use case scenarios are envisioned for eHealth data scientist users of an AC platform.

- Access to AC data sets and services.
- Integration of AC data sets with eHealth research data sets.
- Production of new data sets incorporating fused AC data sets.
- Cross domain application use cases incorporating AC data sets.
- Technical feedback loop to medical professionals and AC researchers/developers.

**Healthcare workers use case scenarios:** In the case of healthcare workers their access and use of an AC platform can be configured and provided in consultation with the medical professional and the administrators of the AC platform. Healthcare workers will generally require access to a subset of the functionality available to the medical professionals.

**Family members use case scenarios:** With reference to the above, the family members and also the producer (User1) will have access to various AC reports and summaries from a non-medical perspective. The focus here is more from a caring, informing, and highlighting of affective states as relevant to the contextual scenario of the subject being monitored by the platform.

This section presented specific use cases relating to the producers of affective data (User1) and it also highlighted the typical features and functionality required by the consumers of the affective outputs from an AC platform. The next section provides a more detailed insight into the functional and non-functional requirements of a conceptual AC platform.

### 3.1.2 Functional and Non-Functional Requirements

For completeness purposes, this section presents an overall set of core functional and non-functional requirements in the context of an overall AC platform solution. It acts as a technical distillation of the various use case descriptions into a generic set of requirements for the conceptual modelling and design processes presented in the remainder of this chapter.

**Core functional requirements of an AC system:** This section presents a number of core functional requirements for a conceptual multi-user AC platform with applied application to the eHealth fields.

- Secure login facility for technical administrators managing the platform.
- Functionality to configure and register AC sensors to an end user (User1).
- Tracking and identification of AC sensors registered on the platform.
- Define and configure the rights and permissions to affective data for all platform users.
- Notify medical professionals of AC sensor setup progress and produce AC sensor installation schedules.
- Services and standards for the set up and configuration of AC sensory interfaces with the platform.
- Views, access and dashboard services relating to the fusion paths of AC sensory data streams.

**AC vision sensors:** The following general functional requirements have been identified for vision sensor technologies deployed to an AC platform.

- Detection of a face in a video frame with a defined bounding box.
- Detection of facial features and landmark data.
- Classification of facial features and landmark data into a number of possible emotional states.
- Interfacing with third party API based cloud services.
- Storage and processing of facial video analytics data by the AC platform.

**AC wearable sensors:** The following general functional requirements have been identified for wearable sensor technologies deployed to an AC platform.

- Detection of physiological data such as galvanic skin response (GSR), heart rate and body temperature.
- Synchronisation and compilation of sensory signals for defined time periods.

- Classification of emotions from processed wearable sensory signal data.
- Interfacing with third party API based cloud services.
- Storage and processing of wearable sensors analytics data by the AC platform.

**AC sensor management and administration:** AC platforms have the potential for the processing of sensory data relating to multiple sensors for multiple users at any one time. This section outlines a number of the functional requirements of the administrative aspects of an AC platform.

- Registration of end-users (User1) that are to be monitored by the AC platform.
- Registration of medical professionals (consultants, nurses, home care etc.) associated with end-users of the AC platform.
- Provide processes for the set-up and management of sensor adaptor registration and allocation to specific end-users.
- Configuration of various analytic levels for access to sensitive related data for all users of the AC platform.

**AC non-functional requirements:** This section presents a number of non-functional requirements relevant to the engineering of an AC platform.

- AC processing and monitoring of end-users must be seamless and require minimum interaction.
- Sensory adaptors must be fault tolerant. Failure in any number of sensors should not impact the overall AC platform performance.
- AC sensor limitations and failures must be engineered for in the overall sensor integration and embedding with the AC platform architecture.

- Privacy must be maintained for all users and data that interface with the AC platform.
- The AC platform must have a high response time with regards to emotion event monitoring and alert services.
- AC platforms must be able to scale up to deal with multiple numbers of concurrent users and the provisioning of addition compute cloud nodes as demand for AC sensory processing grows.
- In relation to eHealth applications, AC platforms must use internationally recognised frameworks and related standards such as Health Level Seven (Health Level Seven International (HL7), 2017) for the exchange, integration, sharing, and retrieval of electronic health information.

This section presented high-level use case scenarios and the formalisation of a number of specific functional and non-functional requirements of a conceptualised AC platform.

## 3.2 Information Modelling of Data Streams

This section describes an approach to the information modelling of sensory data streams and also presents a practical summary of the typical qualities, attributes, ranges, and types of data streams captured using vision and wearable sensory devices.

### 3.2.1 Information Modelling for Affective Computing

In developing an information model for AC, the multimedia stratification model is a significant and associated starting point. With reference to multimedia, video data is a relevant example that has been referenced in the literature. Kankanhalli and Chua (2000) explain how researchers have been trying to develop efficient *techniques to model, index, and retrieve digital video information* (Kankanhalli & Chua, 2000), [p. 68]. This led to the development of the **stratification model** (Smith & Pincever, 1991) for multimedia content. In relation to video content, the stratification process segments the contextual data contained in the video into multiple layers referred to as strata. Figure 3-1 Multimedia Stratification Model below depicts a video segment of a typical news report video.

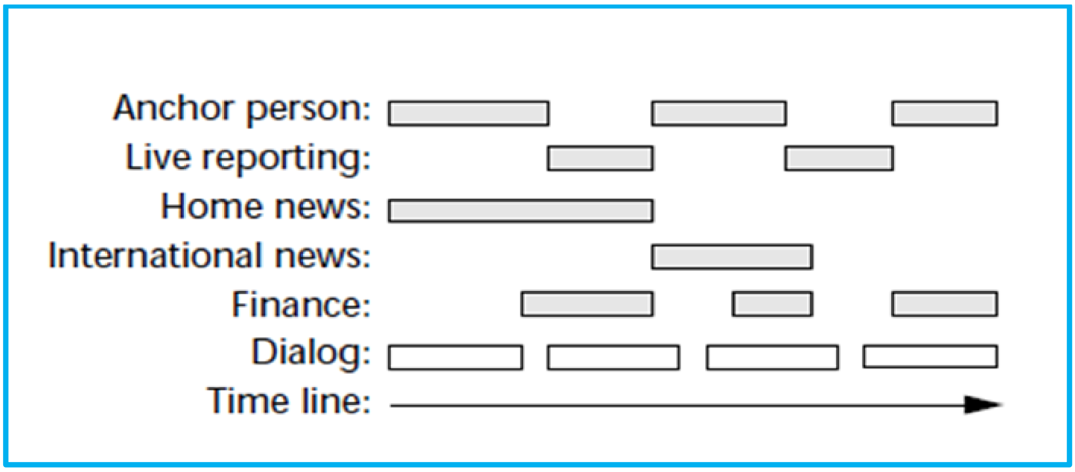



**Figure 3-1 Multimedia Stratification Model (Kankanhalli & Chua, 2000)**

Kankanhalli and Chua (2000) discuss the typical entities that can be modelled from the video segment above and are briefly described below.

**Objects:** These objects may be people in the video such as screen stars, news anchor person, reporters or other objects such as buildings, trucks, bridges, etc.

**Category:** This forms semantic categorical data such as international news, sports or finance related content.

**Structured data:** With reference to video, this structured data provides dates, times and sources of video streams. This can also provide additional data such as photographic and cinematography related contextual data on the specific video scene represented.

**Dialog:** The audio stratum associated with the video represents transcripts from the person objects in the video with the related wording of what was said. The audio stratum may also contain contextual text based explanation of noise sources throughout the video sequence.

In the multimedia stratification model, each stratum *describes the occurrences of a simple concept* (Kankanhalli & Chua, 2000), [p. 68] such as those in the above examples. The various strata may overlap and possess interrelationships which can then provide for the extraction of the semantic meaning of the video at specific points in time. This means that an instance in time of the video content can be flexibly modelled as the union of the entire strata represented.

In relation to the selection of the concepts to be represented by each stratum, the authors highlight that by selecting the *right level of concepts, the extraction of most strata can be automated*, and that this also enables greater modelling capabilities along with the ability to support *most complex retrieval and browsing operations* (Kankanhalli & Chua, 2000), [p. 68]. In summary, Kankanhalli and Chua (2000) define multimedia stratification as a way to model *video content as rich multilayered descriptions parseable by a wide range of applications* (Kankanhalli & Chua, 2000), [p. 68].

The multimedia stratification model is directly applicable to the conceptualisation and development of an AC information model and certain commonalities that relate across both models are summarised below.

**Multimedia stratification model and AC information model commonalities:**

- Both models process multiple sources of data from various modalities.
- The process of fusing disparate data sources into a unified representation is common to both.
- Temporal data is a core concept across both model representations.
- Semantic and contextual data is highly relevant to both models for the creation of applied services and intelligence.
- The resulting model based unified representations can be used to add higher order value and functionality for the development of innovative applications across multiple domains.

Building on the multimedia stratification model above, two specific conceptual stratification models relating to AC systems/platforms were developed and are discussed next.

**Sensor Strata (S-Strata) information model:** The S-Strata relates to an individual mode of affective monitoring. The individual S-Strata is required because any one specific sensing modality may involve one to multiple sensor components contained in the actual device reporting data during a sensing process. Figure 3-2 Sensor Strata (S-Strata) provides a representation of the S-Strata based on the multimedia stratification model discussed previously.

Each of the sensors in the S-Strata are responsible for reporting feature data and all can convey this data at varying time intervals. The sensor processing at this level with reference to Dasarathy's fusion model could incorporate aspects of data in, data out, feature in and feature out processing. Underneath the modality sensors, the coloured lines represent various information processing entities providing applied sensory and affective related contextual data and services.

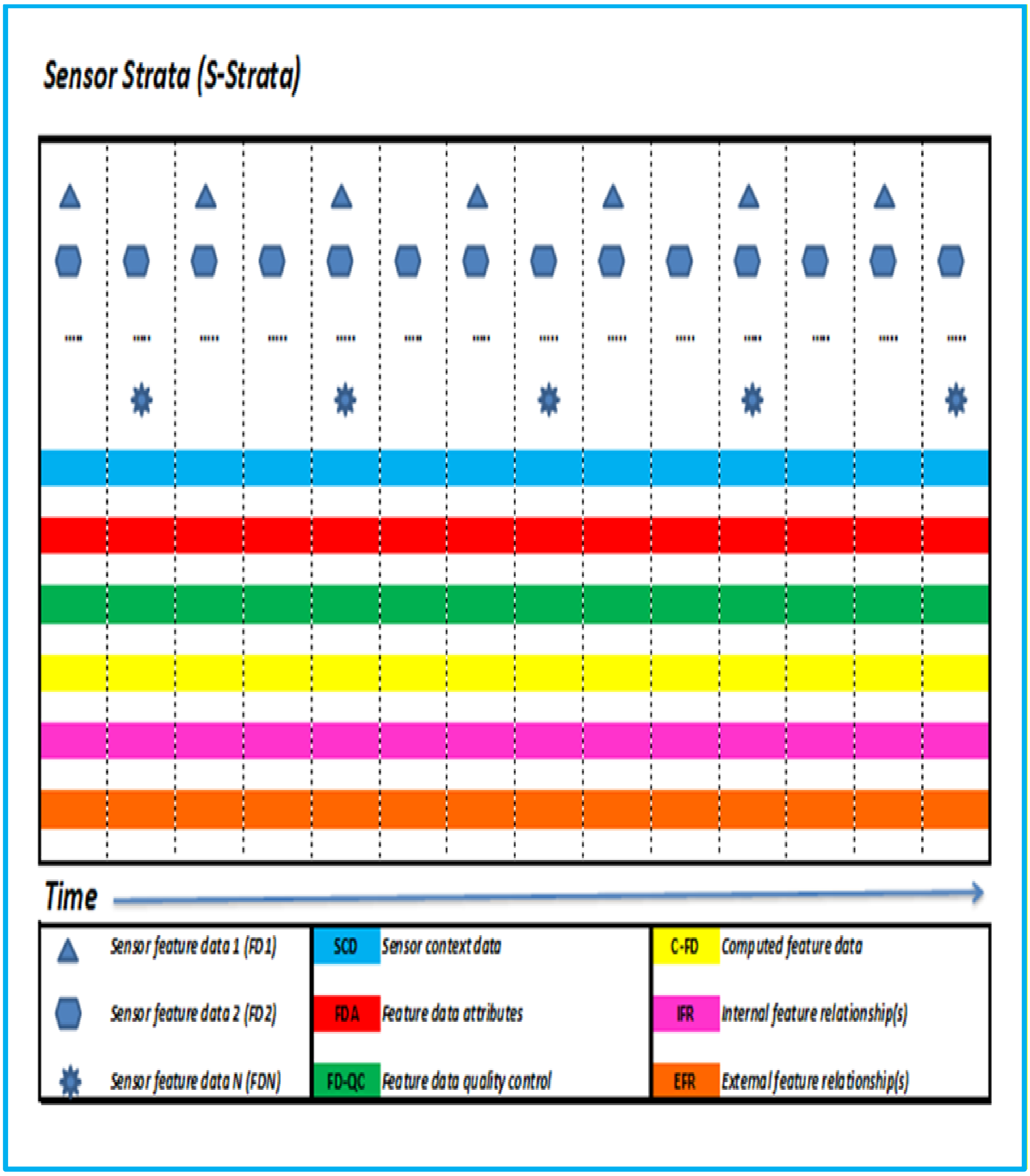



**Figure 3-2 Sensor Strata (S-Strata)**

The sensor context data (SCD) represents contextual data for example in relation to the environment of the monitoring mode. Feature data attributes (FDA) is the specific attributes of the feature data from each sensor. Feature data quality control (FD-QC) relates to distinct quality control processing of the feature data such as accept/reject status of the data reported by the sensors. Computed feature data (C-FD) represents details of new features and associated data that are created from the main sensor input features. Internal feature relationship(s) (IFR) processing entity denotes data about how sensors for the specific sensory modality actually create the various features. This may be the combination of one or more sensor data streams to create other features as in the case of C-FD.

The external feature relationship(s) (EFR) entity provides details on how sensors and their related features data may impact upon other sensory modes and may contribute to feature computation. This could be in the context of an ensemble of vision sensors covering varying angles on a subject or perhaps how a vision sensor could add facial evidence to support an affective decision being made from physiological feature data from a wearable device.

**S-Strata information stratification model example:** With reference to the Figure 3-2 Sensor Strata (S-Strata) and the above explanations of the stratification information processing entities, the following presents a more practical discussion with reference to a typical wearable device such as the Empatica E4 (Empatica, 2017).

In the S-Strata figure the sensor feature symbols along the top could relate to the GSR, Temperature and HR sensors in the E4 wearable. All of these sensors capture physiological data and process this data at varying time intervals. Each of these sensors may also have their own embedded quality control mechanisms to ensure pre-defined manufacturer validity of the reported sensor data.

The first blue line in the stratification layers relates to the sensor context data (SCD). This provides for data on the contextual setting of the actual sensor. This may convey indoor or outdoor data capture status, it may detail where the wearable is placed on the body of the subject or it may also provide health related contextual data on the subject(s) being monitored.

The red line, feature data attributes (FDA) relates to the specific attributes of feature data from each of the E4 sensors. This can be used to control noise in the monitoring environment as the attributes can define typical ranges of acceptable or rejectable data (min/max) provided by a specific sensor type. It also provides further details on the nature and meaning of the feature data (body skin temperature, skin conductance, body movement, etc.) produced by the various sensor components in a particular AC sensory device.

The feature data quality control (FD-QC) represented by the green stratification line formally represents low level signal processing engineering that may be part of the AC sensory device itself. For example the E4 has embedded proprietary algorithms that can deal with noise artifacts that may impact on the GSR and HR sensor data streams. In the S-Strata, this stratification layer may also work at a higher level of abstraction and may be used to decide to accept or reject feature data streams from specific sensors based on other reasons such as those defined and communicated by the SCD and FDA stratification layers.

The yellow line represents computed feature data (CFD) and with reference to the E4 wearable this may involve the computation of additional features using the inputs of the GSR, Temperature, HR, Interbeat Interval (IBI) or Accelerometer data to produce new features. For example this may be a feature that combines HR in conjunction with Accelerometer data to create a specific movement related feature data stream. In the event of new features being produced by the CFD stratification layer, then the pink internal feature relationships (IFR) stratification layer provides details of the methods, processes and techniques that are deployed in order to compute any new feature data. In the case of the E4 the role of the IFR is to provide explanation of the new features created from the existing raw data streams.

Finally, the orange stratification line representing external feature relationships (EFR) provides for scenarios where feature data from one type of AC sensor may be used to support decision making in relation to other sensors. For example the EFR layer may enable the provision of the E4 GSR, HR and Temperature sensor data streams to an AC vision sensor as part of the AC decision making fusion process.

All of the stratification layers discussed with reference to the E4 wearable provide practical examples of how the more theoretical aspects of Dasarathy's five fusion processing modes are applied in an AC sensor processing context. In particular, the various stratification concepts presented in the S-Strata model all incorporate elements of the data, feature and decision fusion modes discussed by Dasarathy.

In summary, the S-Strata information model signifies that within any AC analytical modality, one or any number of embedded device specific sensors may be involved. The model describes the temporal aspects of the sensors incorporated into the specific modality and also provides for contextual and semantic representations that deal with both internal and external feature relationships.

The S-Strata is a useful conceptual information model when considering the AC functionality of an individual sensor modality. To expand the conceptualisation and thinking to a multi-sensory fusion level, the S-Strata model is now incorporated into a higher level stratification information model to be referred to as the Affective Computing Strata (AC-Strata).

**Affective Computing Strata (AC-Strata) information model:** The AC-Strata model represents individual affective monitoring modalities such as vision, wearables, voice, gait, computer inputs and other sensors. All these sensory modes report at varying time intervals and must be combined in a unification/fusion process. In Figure 3-3 Affective Computing Strata (AC-Strata) below each individual sensor in the stratification model is referenced as Sensor Strata (SS) one to N, [SS short for the S-Strata information model].

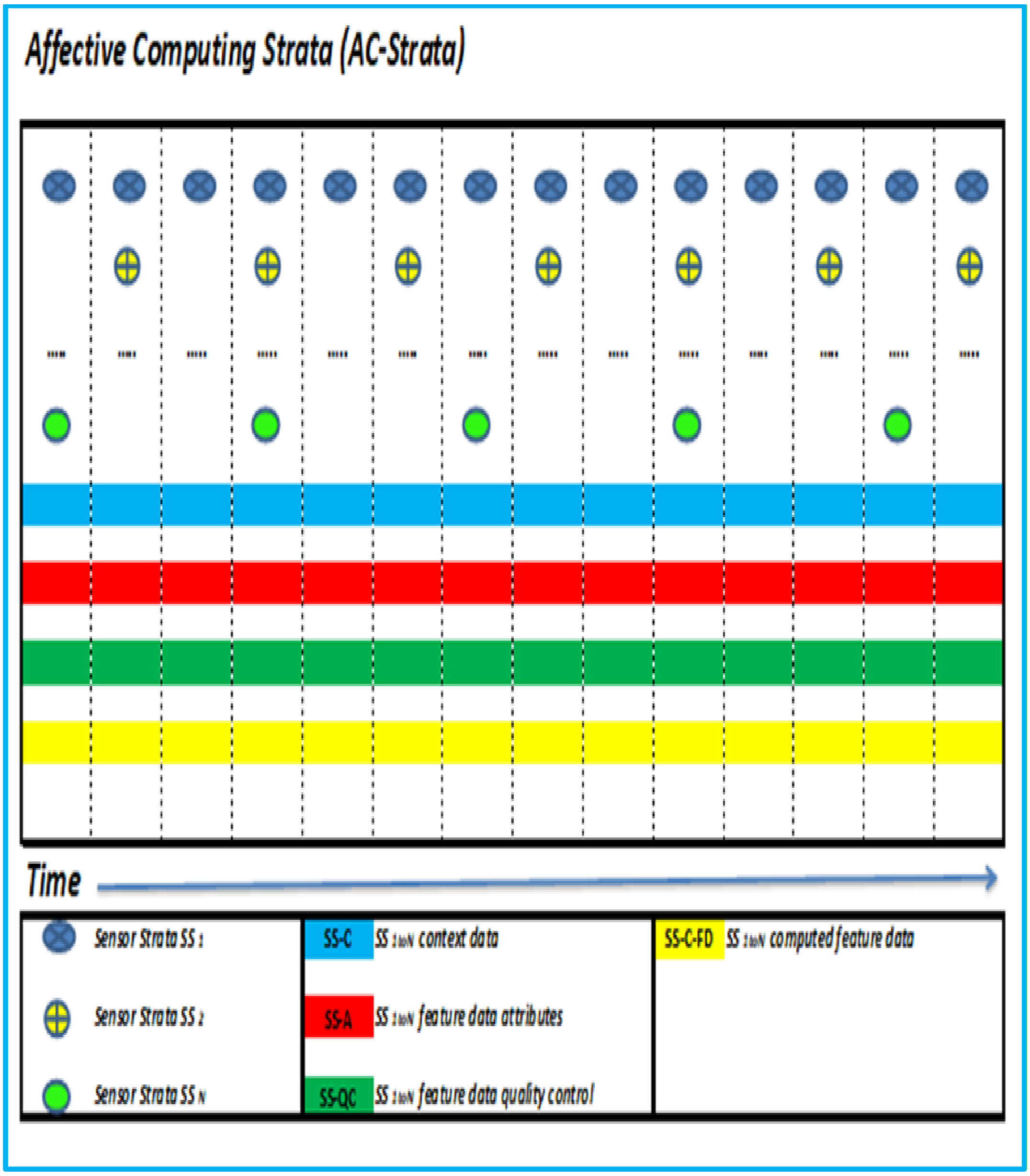



**Figure 3-3 Affective Computing Strata (AC-Strata)**

In the AC-Strata model, the SS context data (SS-C), SS feature data attributes (SS-A), SS feature data quality control (SS-QC) and the SS computed features data (SS-C-FD) all generally represent the same forms of data as discussed in relation to the S-Strata model and are discussed below in an AC multi-sensory fusion context.

**AC-Strata information stratification model example:** This section provides a practical discussion on the various stratification layers contained in the AC-Strata in Figure 3-3 Affective Computing Strata (AC-Strata). The blue line in the AC-Strata represents the context data similar to the S-Strata but in a multi-sensor context. The SS-C stratification layer provides contextual data (SS-C) in relation to the full range of sensors deployed for an AC platform. The SS-C may gather data from the underlying S-Strata and there may also be higher level contextual data on the AC application domain or personalisation contextual data on the subject(s) being monitored.

The AC-Strata feature data attributes (SS-A) compiles all of the attributes on all features produced across the multi-sensor network. Again this data may arise from each sensor's S-Strata or indeed additional feature data attributes may be generated in relation to the combination of sensors working together in an AC multi-sensor processing capacity.

The green line, feature data quality control (SS-QC) provides for more applied feature or decision related control of the AC data streams provided by the various sensors. The interrelationship and configurations of the SS-C and the SS-A may be an influence on the acceptance or rejection of AC sensor feature data or decisions. The SS-QC stratification layer may also be influenced by aspects of the application domain (certain affective states may not be valid or acceptable) or more personalised knowledge of the subject(s) (certain affective states may not be valid or accepted at certain times/conditions/locations) being monitored.

The SS computed feature data (SS-C-FD) represented by the yellow stratification line provides for the computing of additional feature data, features or decisions based on the outputs from each individual sensor. This provides for applied fusion related pre-processing of all the sensor outputs (data, features, decision) in preparation for higher level AC processing via statistical, machine learning, semantic and ontological reasoning processes.

At this higher level of abstraction in the AC-Strata model, the information processing entities and their resulting data and knowledge representations are most specifically related to the multi-modal fusion aspects and the semantics of the use case domain(s) under development.

In summary, the above used an established stratification information model from multimedia and applied this to the AC domain while also applying the underlying theoretical and conceptual aspects of Dasarathy's flexible data fusion model. This resulted in the S-Strata model which is used here to represent individual sensory modalities. S-Strata was then used and applied to the development of a higher level stratification model called AC-Strata which incorporated and reapplied defined S-Strata concepts from a multi-sensory fusion perspective.

The S-Strata and AC-Strata information stratification models provide a conceptual formalisation and they will both be revisited in the remaining sections of this chapter. Before that, the next discussion on information modelling of data streams directly relates to the S-Strata model. It provides details on the typical data types, data attributes, and the properties of both vision and wearable sensor modalities.

### 3.2.2 Information Model of Vision Data Streams

This section presents discussion on sensors and the data types, attributes, and various properties associated with vision modality devices that may be used for AC research.

The Figure 3-4 Intel RealSense SR300 Front View is from the Intel RealSense SR300 technical specification and demonstrates a modality device for vision that contains multiple sensors. The SR300 is designed as a standalone or embedded system component offering 3D vision capabilities to various objects such as computers, robots, and cars.

The SR300 incorporates a number of vision sensors including a colour camera, infrared camera and an infrared laser projector. The SR300 demonstrates how a single sensory modality device may itself incorporate any number of modality related embedded sensors with applied functionality. Further technical details in relation to the in-built sensor types are outside the scope of this section but are available in the SR300 technical specification manual (Intel, 2017).

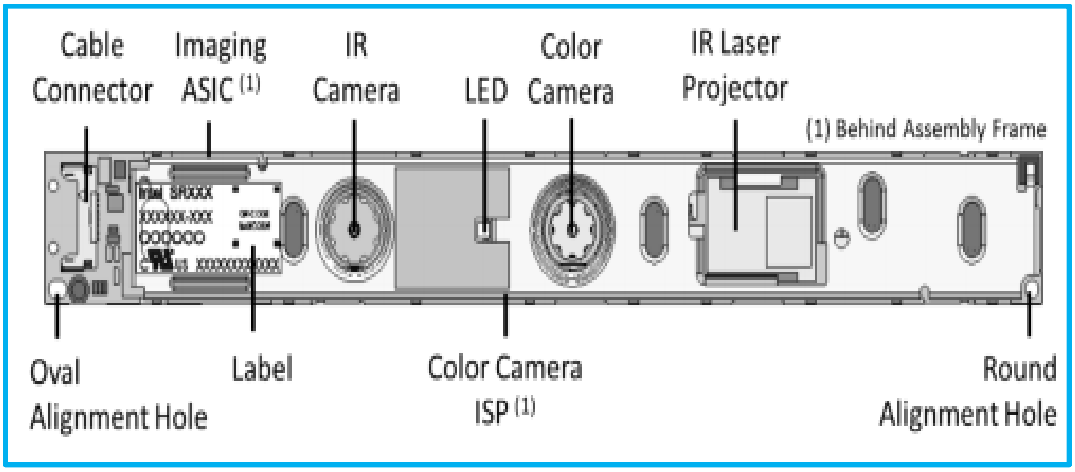



**Figure 3-4 Intel RealSense SR300 Front View (Intel, 2017)**

The remainder of this section presents a selection of the types, attributes, and various properties associated with vision feature data streams.

**Facial Landmark Points:** Facial landmarks are defined as the detection and localisation of certain key points on a human face. They are also known as vertices or anchor points. The points may be grouped around the eyebrows, eyes, nose, mouth and the jaw line. The number of landmark points processed by vision systems may vary depending on the platform capabilities.

The Figure 3-5 Vision Facial Landmark Tracking represents the facial landmark tracking of the Affectiva Affdex platform (Affectiva, 2017), while the Excel graphic Figure 3-6 Vision Facial Landmark Data Extract is an extract from a CSV file that computes sixty eight 2D facial landmark points (Healy, Keary, & Walsh, 2016) per frame of facial vision data.

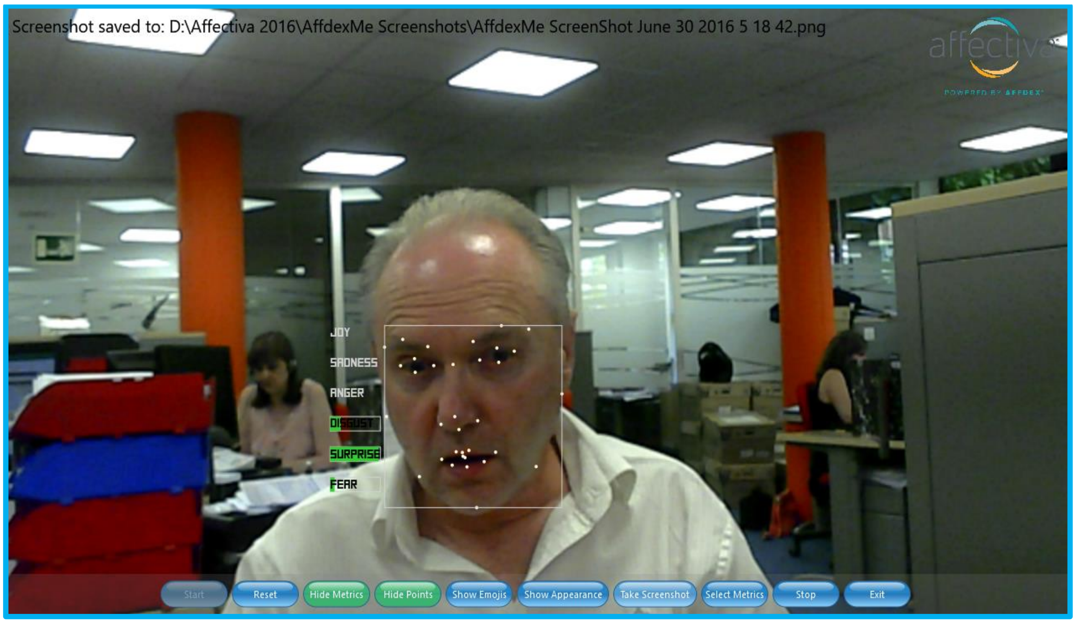



**Figure 3-5 Vision Facial Landmark Tracking**

**Emotion ID:** A range of AC vision based SDKs provide FACS based algorithms that process the facial landmark points data for emotional classification. This data is then processed into an Emotion ID data type which can be used to return an emotional classification such as contempt, fear, anger, surprise, disgust, joy and sadness.

| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | **Timestamp** | **Frame** | **Point 1** | **Point 2** | **Point 3** |
| 2 | Time: 19:16:4 | 30 | 199.416 339.517 | 200.416 356.546 | 203.069 373.371 |
| 3 | Time: 19:16:6 | 61 | 203.27 346.04 | 203.313 360.924 | 204.242 376.155 |
| 4 | Time: 19:16:7 | 92 | 205.14 343.189 | 206.355 360.666 | 208.201 378.365 |
| 5 | Time: 19:16:8 | 123 | 216.017 344.231 | 217.557 360.157 | 219.528 376.5 |
| 6 | Time: 19:16:9 | 154 | 203.945 344.899 | 205.596 361.56 | 208.321 379.126 |
| 7 | Time: 19:16:10 | 185 | 199.767 342.447 | 201.433 359.227 | 203.831 376.402 |
| 8 | Time: 19:16:11 | 216 | 199.496 341.1 | 200.851 358.226 | 203.677 375.322 |
| 9 | Time: 19:16:12 | 247 | 200.15 341.061 | 200.835 358.475 | 203.344 376.044 |
| 10 | Time: 19:16:14 | 278 | 200.111 341.656 | 200.666 358.708 | 203.113 375.877 |
| 11 | Time: 19:16:15 | 309 | 200.609 342.337 | 201.706 359.194 | 204.159 376.794 |
| 12 | Time: 19:16:16 | 340 | 202.132 341.487 | 202.605 358.106 | 205.176 375.074 |
| 13 | Time: 19:16:17 | 371 | 201.663 341.344 | 202.288 358.439 | 204.319 375.292 |
| 14 | Time: 19:16:18 | 402 | 200.736 341.817 | 201.207 358.772 | 203.621 376.188 |
| 15 | Time: 19:16:19 | 433 | 206.928 337.847 | 208.321 354.882 | 210.81 371.695 |

**Figure 3-6 Vision Facial Landmark Data Extract**

**Face ID:** AC vision systems can track multiple faces that are generally given a numeric value starting at zero for the first face identified in the vision data frame. Systems will vary in terms of the number of faces that can be tracked and there is also the problem of facial recognition if you want to keep track of the same individual for monitoring purposes.

**Sentiment:** This data feature classifies the emotion ID as being one of positive, negative or neutral values.

**Valence:** AC vision sensors can also process valence values ranging from -100 to 100. Valence is an attempt to measure the positive or negative nature of an AC monitored experience in relation to a subject in a video frame. Valence provides feedback values on an overall experience relating to a subject. Valence values from 0 to 100 indicate a neutral to positive experience for a subject. Values from -100 to 0 indicate a negative to neutral experience.

**Intensity:** The intensity feature data values can indicate the presence likelihood of the detected emotion state and ranges from 0 to 1.

**Evidence:** Evidence values can range between -5 and 5. They represent the odds in 10-based logarithmic scale of a target emotion expression being present.

**Engagement:** This is a measure of facial muscle activation that can be used to identify the expressiveness in a person's face. The values could range from 0 to 100.

**Facial Expressions:** Some AC vision platforms provide additional facial expressions which may not directly relate to an emotional state. For example the Affdex (Affectiva, 2017) platform provides for tracking of feature data that include expressions of eye closure, attention, mouth open, smile and smirk.

**Head Orientation:** This uses Euler Angles (Weisstein, 2017) in the computation of pitch, yaw and roll estimations of the subjects head position in a 3D space. With reference to the Figure 3-7 Vision Euler Angles, the yaw value if positive indicates that the face is looking to the right, the pitch value if positive indicates that the face is looking up while the roll value if positive indicates that the face is leaning towards the right shoulder (Intel, 2017) .

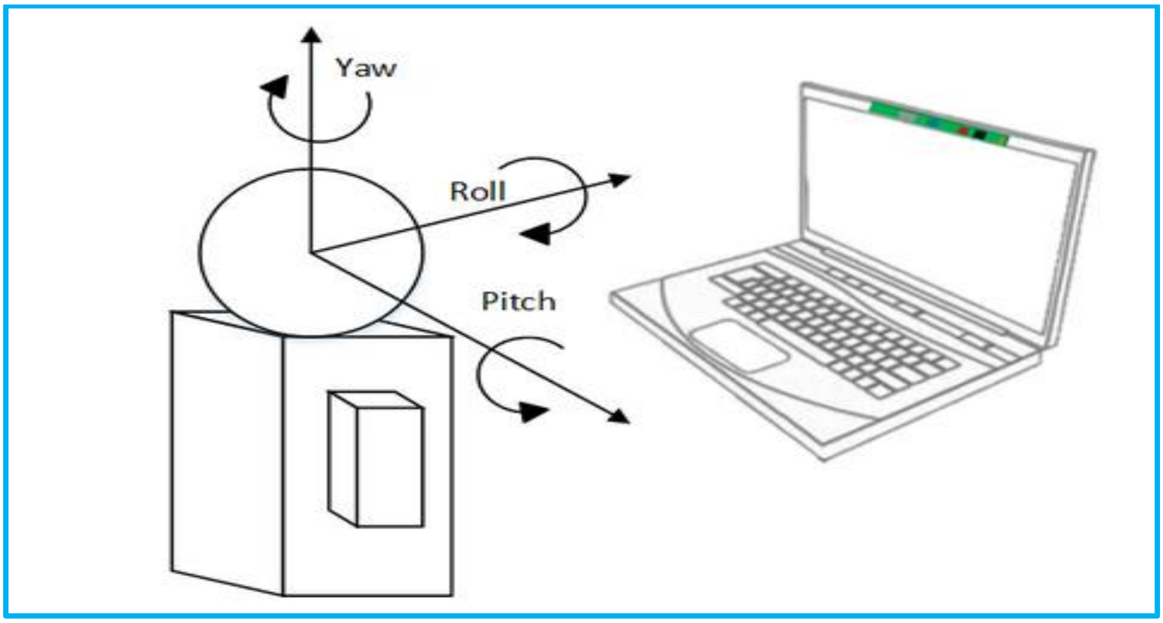



**Figure 3-7 Vision Euler Angles (Intel, 2017)**

**Interocular Distance:** This is a distance measurement between the two outer eye corners of the subject.

**Age:** This feature provides an estimate of the age range of the subject in the video frame data.

**Ethnicity:** This is an advanced feature provided by the Affdex platform and is a function of its global classification across many cultural facial expressions. Affdex currently supports the following classification of ethnic backgrounds, Caucasian, Black African, South Asian, East Asian and Hispanic.

**Gender:** Vision classifier aims to identify the gender expression of the subject in the frame data.

**Glasses:** Reported as a confidence value as to whether the subject is wearing glasses or not.

**Timestamp:** Timestamp data can be associated with the emotion data that is detected.

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | TimeStamp | FaceId | Interocular Distance | Glasses | Gender | Pitch | Yaw | Roll | Joy | Fear | Disgust |
| 2 | 8.0640 | 0 | 118.4702 | no glasses | male | -6.9062 | -6.7985 | -15.0556 | 0.0016 | 0.0053 | 0.001 |
| 3 | 8.1300 | 0 | 124.35 | no glasses | male | -3.3467 | -3.8246 | -4.9193 | 0.0006 | 0.0128 | 0.0011 |
| 4 | 8.1640 | 0 | 122.6107 | no glasses | male | -2.628 | -3.7981 | -4.3923 | 0.0005 | 0.0146 | 0.0012 |
| 5 | 8.2310 | 0 | 122.1222 | no glasses | male | -4.4953 | -2.463 | -2.4132 | 0.0005 | 0.0152 | 0.0083 |
| 6 | 8.2980 | 0 | 121.4271 | no glasses | male | -3.7555 | -3.1857 | -1.6808 | 0.0005 | 0.0178 | 0.0412 |

**Figure 3-8 Vision Feature Data 1 of 2**

The Excel figures Figure 3-8 Vision Feature Data 1 of 2 and Figure 3-9 Vision Feature Data 2 of 2 represent research trials of the Affectiva Affdex AC vision platform and demonstrates the types, data values and range of the available feature data from their vision SDK platform.

| | L | M | N | O | P | Q | R | AC | AD | AE | AF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Sadness | Anger | Surprise | Contempt | Valence | Engagement | Smile | MouthOpen | Smirk | EyeClosure | Attention |
| 2 | 0.0015 | 0.0645 | 0.2486 | 98.757 | 0 | 46.3067 | 0.0001 | 0.031 | 99.9998 | 0.0023 | 95.4362 |
| 3 | 0.0012 | 0.0072 | 1.062 | 98.7569 | 0 | 86.099 | 0 | 0.0242 | 99.9999 | 0 | 97.4296 |
| 4 | 0.0013 | 0.0047 | 1.2905 | 98.757 | 0 | 87.7803 | 0.0001 | 0.0129 | 99.9999 | 0 | 97.4429 |
| 5 | 0.0032 | 0.0019 | 1.3443 | 98.7569 | 0 | 45.7127 | 0 | 0.0058 | 99.9999 | 0 | 98.0303 |
| 6 | 0.0058 | 0.0008 | 1.716 | 98.7569 | 0 | 16.6999 | 0 | 0.0035 | 99.9999 | 0 | 97.731 |
| 7 | 0.0072 | 0.0005 | 2.003 | 98.7569 | 0 | 7.8854 | 0 | 0.0036 | 99.9997 | 0 | 97.7502 |
| 8 | 0.0089 | 0.0003 | 2.3586 | 98.7568 | 0 | 5.2981 | 0 | 0.0039 | 99.9992 | 0 | 97.6002 |

**Figure 3-9 Vision Feature Data 2 of 2**

The objective of this section was to provide a deeper insight into the types of data streams processed by AC vision modalities. The next section investigates the typical data streams associated with wearable sensors.

### 3.2.3 Information Model of Wearable Data Streams

This section presents discussion on sensors and the data types, attributes, and various properties associated with physiological wearable devices that may be used for AC research.

**GSR/EDA:** Data from the GSR sensor in Figure 3-10 Wearable GSR/EDA Data is expressed in microSiemens (ConvertUnits.com, 2017). For example the Empatica E4 has a typical sampling frequency of 4 Hz with a range of 0.01 microSiemens to 100 microSiemens. Resolution relates to the smallest change a sensor is capable of detecting and in the case of the E4 this is approximated as 900 picoSiemens or 0.0009 microSiemens[11].

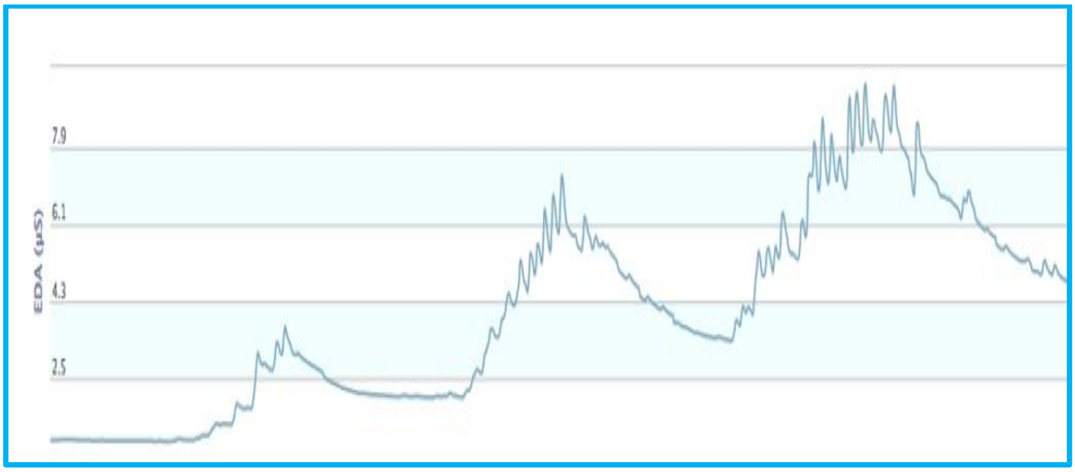



**Figure 3-10 Wearable GSR/EDA Data**

**Photoplethysmography sensors (PPG):** The PPG sensor illuminates the skin and measures the light reflected and is used in the calculation of the heart rate and related values (Allen, 2007). PPG is also known as Blood Volume Pulse (BVP) (Jones, 2016) in the scientific literature. The sensor used in the E4 has a sampling frequency of 64 Hz with two green and two red light-emitting diodes (LEDs) and two photodiode (Learning About Electronics, 2017) units. The sensor output produces the difference of light that is sensed between oxygenated and non-oxygenated peaks in arterial blood flow. PPG uses the fact that blood is red and that it will reflect red light and absorb green light. Thus when the heart beats, the blood flows and this increases the green light absorption. Between heartbeats the green light absorption is less (Apple Inc., 2017). The PPG sensor can also have algorithms for the removal of motion artifacts that may impact the reliability of the signal and can also tolerate changing external lighting conditions.

[11] https://www.convertunits.com/from/picosiemens/to/microsiemens

A typical PPG sensor can have an output resolution of 0.9 of a nanoWatt. The SI prefix (National Physical Laboratory, 2017) nano represents a factor of $10^{-9}$, or in exponential notation, 1E-9. Figure 3-11 E4 38 Hours of Heart Rate Recording from PPG Sensor with time on the x axis and PPG on the y axis shows the computation from the PPG sensor data with heart rate increasing during the day and reducing during the night periods (Garbarino, Lai, Bender, Picard, & Tognetti, 2014).

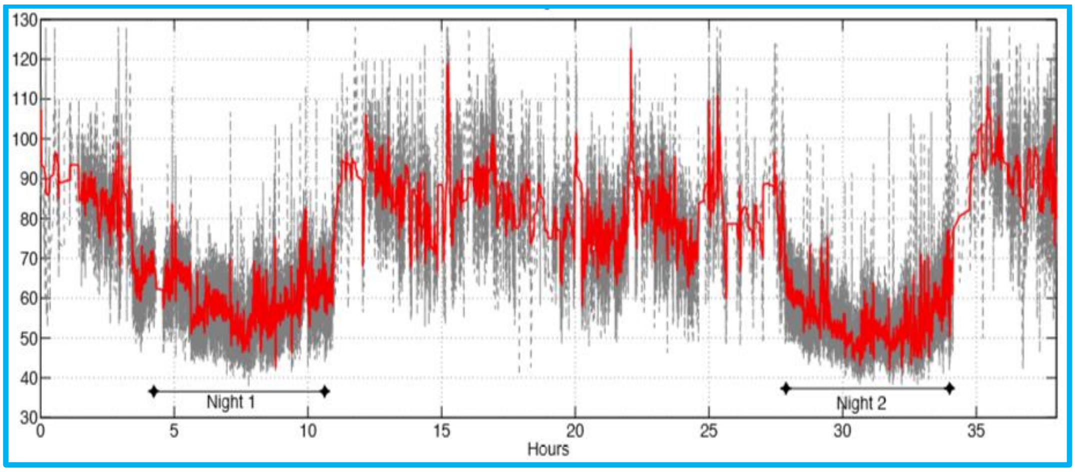



**Figure 3-11 E4 38 Hours of Heart Rate Recording from PPG Sensor (Garbarino, Lai, Bender, Picard, & Tognetti, 2014)**

**Inter-Beat Interval (IBI) and Heart Rate (HR):** The heart rate can be computed on a wearable by *detecting peaks (beats) from the PPG and computing the lengths of the intervals between the adjacent beats. The Inter-Beat Interval (IBI) timing is used to estimate the instantaneous heart rate as well as to estimate the average heart rate over multiple beats* (Empatica, 2017).

The typical usage scenario for the E4 wearable device is in the recording of the resting heart rate during everyday scenarios. PPG sensor heart rate data is not suitable in the event of running or physical activity. The measurement units are in seconds and the resolution is to 1/64 seconds (0.015625 of a second). Figure 3-12 Wearable Blood Volume Pulse (BVP) with time on the x axis and BVP on the y axis shows the peaks identified in the BVP which are used in the heart rate computations in a wearable device.

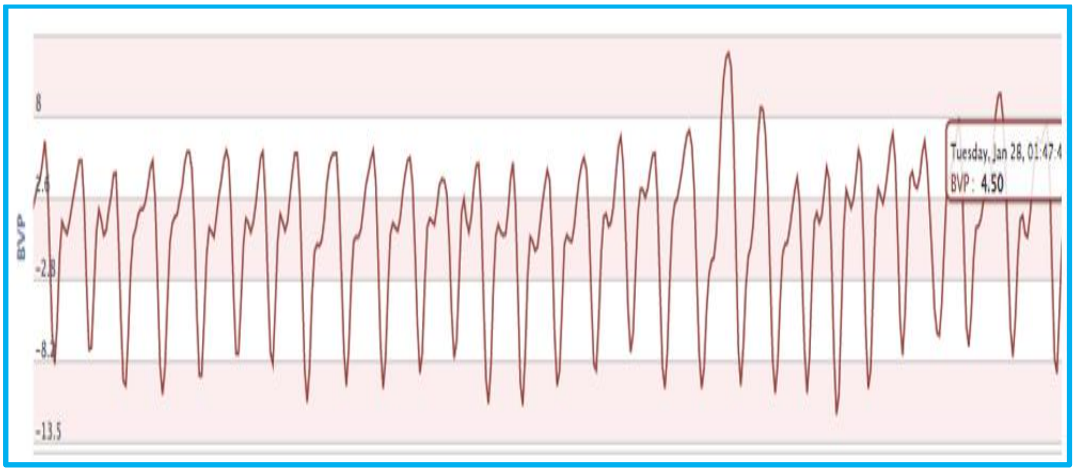



**Figure 3-12 Wearable Blood Volume Pulse (BVP) (Empatica, 2017)**

**Temperature:** Skin temperature is derived from an optical temperature sensor placed on the wrist. Temperature sensors can use an infrared thermopile (Karaki & Polyzoev, 2014) for the non-invasive calculation of temperature. The E4 temperature sensor data displayed in Figure 3-13 Wearable Temperature Data with time on the x axis and Temperature on the y axis has a sampling frequency of 4 Hz and a signal resolution of 0.02°C. The temperature can range from - 40 to 85°C for ambient temperature (if available) and -40 to 115°C for skin temperature. Accuracy can be within +/- 0.2°C within the range of 36 to 39°C.

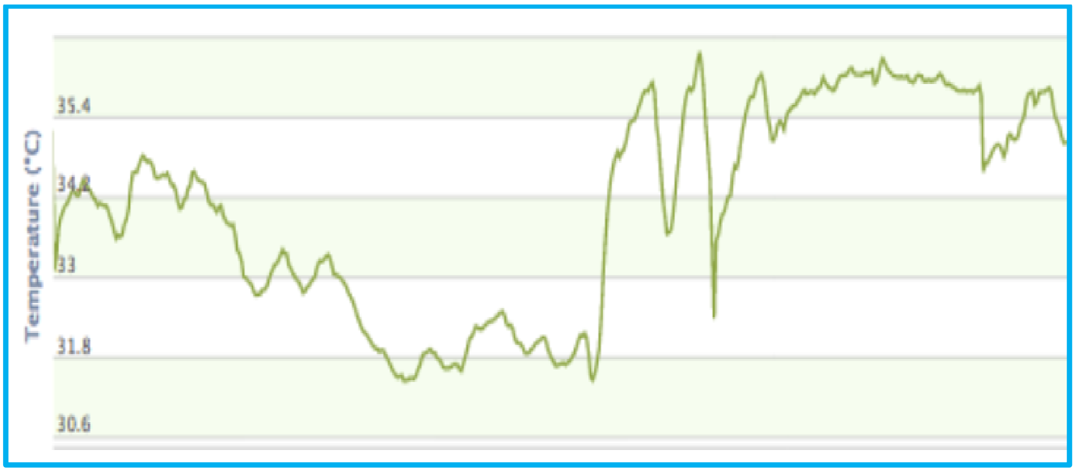



**Figure 3-13 Wearable Temperature Data (Empatica, 2017)**

**Other sensors found in wearable devices:** This section provides an overview of other types of sensors found in physiological wearable devices.

**Accelerometer:** Accelerometer sensors provide 3-axis acceleration data as X, Y, Z measurements that can typically range from -2g to 2g, -4g to 4g, -8g to 8g (SparkFun, 2017). Devices can provide different sampling frequencies such as 62, 32 or 8 Hz. Resolution in the case of the E4 for example is defined as eight bits of the selected range. For a range of -2g to 2g this is worked out as 4/256 = 0.0156250g.

**Distance:** Can provide the total distance in centimeters, current speed in centimeters per second (cm/s), current pace in milliseconds per meter (ms/m), and the current pedometer mode (such as walking or running) with a frequency of 1 Hz.

**Subject Contact:** Can identify the current state of the wearable as being worn or not worn.

**Barometer:** Provides the current raw air pressure in hPa (hectopascals) and raw temperature in degrees Celsius with a frequency of 1 Hz.

**Altimeter:** Provides the current elevation data like total gain/loss, steps ascended/descended, flights ascended/descended, and elevation rate with a frequency of 1 Hz.

**Timestamp data:** The timestamp data from a wearable is represented in seconds as the time interval between the sample received and the reference date 01 January 1970, GMT. Figure 3-14 Wearable Timestamp Data is an extract of the 4 Hz GSR data in CSV file format from the E4 with the timestamp highlighted.

Timestamp data can easily be converted using an Excel formula into the relevant date and time representation.

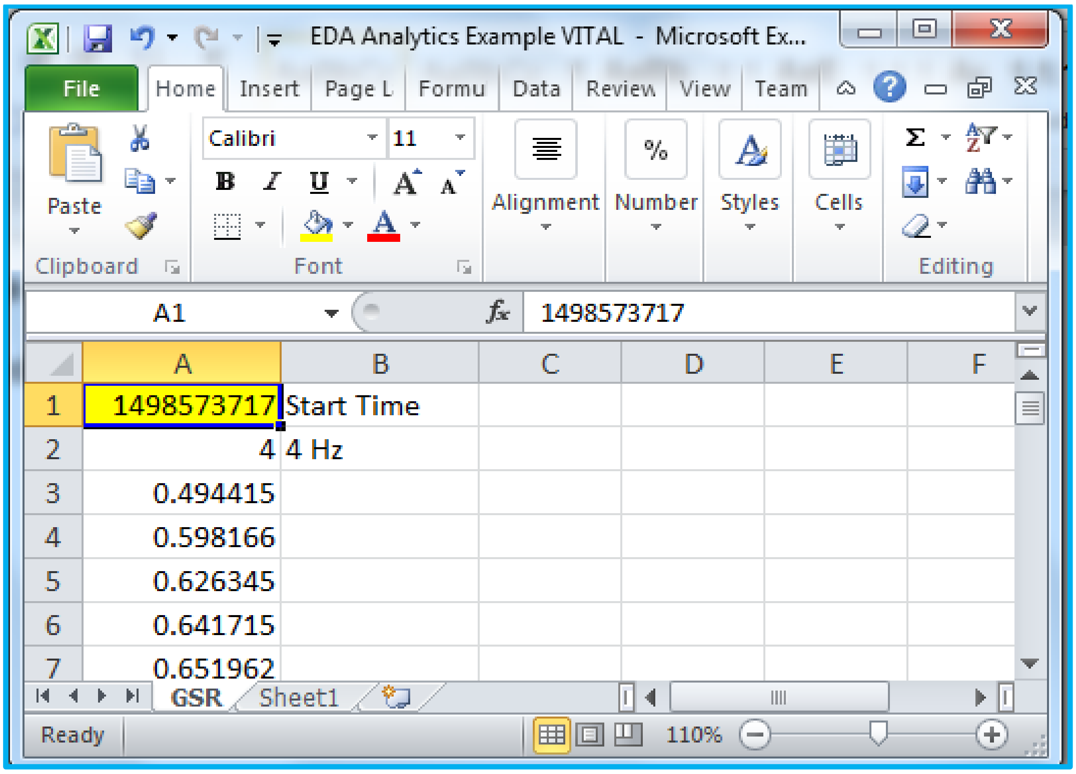



**Figure 3-14 Wearable Timestamp Data**

### 3.2.4 Information Modelling Summary

The objective of this section was to introduce an information modelling framework that could act as a reference point in the further conceptualisation of a multi-sensory fusion AC platform. This resulted in the creation of the S-Strata and AC-Strata information models that were grounded in the stratification model from earlier multimedia related video stream research and the Dasarathy data fusion model.

Having positioned and explained both of the AC related stratification models the next two sections looked into the typical data streams found in AC sensors. These sections focused exclusively on vision and wearable sensors and the details presented will be of benefit to the reader for the later chapters in this thesis.

## 3.3 Affective Computing Sensory Fusion

Chapter two presented an insight into the scientific and technological aspects of sensory fusion. This section revisits multi-modal sensory fusion with a reminder of the fusion possibilities and the more practical aspects for consideration. It also expands on the S-Strata information model discussed above and presents a proposal for a generic conceptual model for AC sensory fusion.

### 3.3.1 Sensory Fusion Process

The two main techniques presented in chapter two were feature and decision level fusion. In relation to feature-level fusion, *the feature sets originating from multiple biometric sources are consolidated into a single feature set by the application of appropriate feature normalization, transformation, and reduction schemes* (Li & Jain, 2009), [p. 597]. Feature level fusion has the advantage of only one learning stage and it also benefits from the analytic potential of the common data that has been fused from the sensors (Snoek, Worring, & Smeulders, 2005). Production of the related feature set *typically requires the use of dimensionality reduction methods and, therefore, feature-level fusion assumes the availability of a large number of training data* (Li & Jain, 2009), [p. 597].

The alternative decision fusion process involves the selecting of *one hypothesis from multiple M hypotheses given the decisions of multiple N sensors in the presence of noise and interference* (Li & Jain, 2009), [p. 593]. This scheme could also be considered as the fusion of classifiers whereby the output decisions of prior individual sensory classifications are further classified in a form of higher level upstream classification. As discussed in chapter 2, the literature can vary in terms of feature and decision level fusion and in various AC research a dual approach can help with the identification and justification of the best scheme to be used.

Given the above fusion schemes, typical AC sensory devices open up some interesting considerations. For example, in relation to the capture of facial expression data for emotion recognition, vision devices can range from Web cameras, high definition phone cameras to advanced 3D depth cameras. The feature sets captured by these devices can also then be processed by customised, proprietary or open source AC vision algorithms/classifiers.

In the case of proprietary and open source classifiers, access to the raw feature data sets may not always be possible. This fact is an important consideration and is a factor in relation to AC vision sensors in use today. For example services from AC vision providers will produce not only the emotion classification but can also deliver many additional appearance features in relation to a subject.

Physiological sensors are increasingly used in AC research but their origins are in the medical domain. Dedicated AC services and platforms for wearable sensors are generally not readily available today. Commercial companies like Shimmer (Shimmer, 2015) and Empatica (Empatica, 2017) are changing this but the overall availability of recognised AC algorithms for physiological based emotion classification is still very much a developing field. Thus researchers are still building, establishing and testing their own models for affective classification of data from physiological sensors.

In relation to other sensory modalities such as EEG, voice, gait/body movement, text, computer inputs, gestures, and object interactions it can be expected to be sometime before they reach the AC maturity level of computer vision sensors.

In the case of this PhD research, the early focus on vision and wearable sensors introduces an interesting scenario when it comes to data fusion. Vision is by far one of the most mature AC sensor technologies and many classification options are available. On the other hand, the understanding and classification of emotions from physiological signals (wearables) and indeed other modalities is less well understood and developed.

In relation to AC sensory data fusion, the current and near-term scenario is a combination of devices that given sensory input the device itself uses on-board hardware or SDK/API algorithms to perform emotion classification or the device produces a feature set that is used for follow on processing by customised AC classification algorithms.

Given the advances in vision, similar possibilities may exist for wearable sensors with on-board AC algorithms and access to established SDK/API based classifiers. The key point is that the AC research community today is faced with the positive prospect of ever increasing combinations of sensory devices that will possess either full or partial affective intelligence in the future.

So how does this current scenario relate to the implementation of feature and decision level fusion schemes? From a feature level fusion perspective, as discussed above, it may not always be possible to get access to raw feature data sets from AC sensor manufacturers. This means that the creation of the feature level fusion vector with the required data may not be possible. This also means that correlation of feature data across multiple sensors would be limited.

Decision level fusion is perhaps a best fit when there is a combination of sensors with varying level of affective intelligence. This will require the development/enhancement of classifiers for the sensors with none/partial affective intelligence and the integration of these classifier decisions into the ensemble with the other AC enabled intelligent sensors in the mix. Once all sensors have an AC related decision making capability, higher level voting/probability and further classification techniques will need to be applied in the affective decision making process.

The discussion thus far has outlined practical considerations the must be taken into account in the realisation of future AC platforms. Feature and decision level fusion relate to the S-Strata information model in the context of what the S-Strata produces. At a decision level it will deliver an affective classification decision with related supporting data while at a feature level it will deliver a feature data set for onward amalgamation with other sensor datasets.

The S-Strata model applies regardless of the fusion scheme implemented and it also incorporates many other sensor considerations. These considerations include data interference/noise, ambient temperatures, data loss, validity, performance, humidity, duplicate data and many other factors which can impact on the data that is used in the sensors affective analytical processes.

With the above discussions in mind, the next section aims to apply the high-level S-Strata information model to the creation of a more practical, functional and technical representation of a generic conceptual framework for AC sensory data fusion.

### 3.3.2 Conceptual Framework for AC Sensory Fusion

This section describes a generic sensor adaptor process that uses the S-Strata information model to present the lower level layers of a conceptual AC architecture that provides for multi-sensor fusion.

The Figure 3-15 Sensor X Adaptor Processing below represents a conceptual framework for generic sensory adaptor processing. For descriptive purposes Sensor X refers to any form of sensory modality (vision, physiological …) device used for AC. The concept of adaptor encapsulates both the hardware and software required for the configuration of Sensor X for an AC platform.

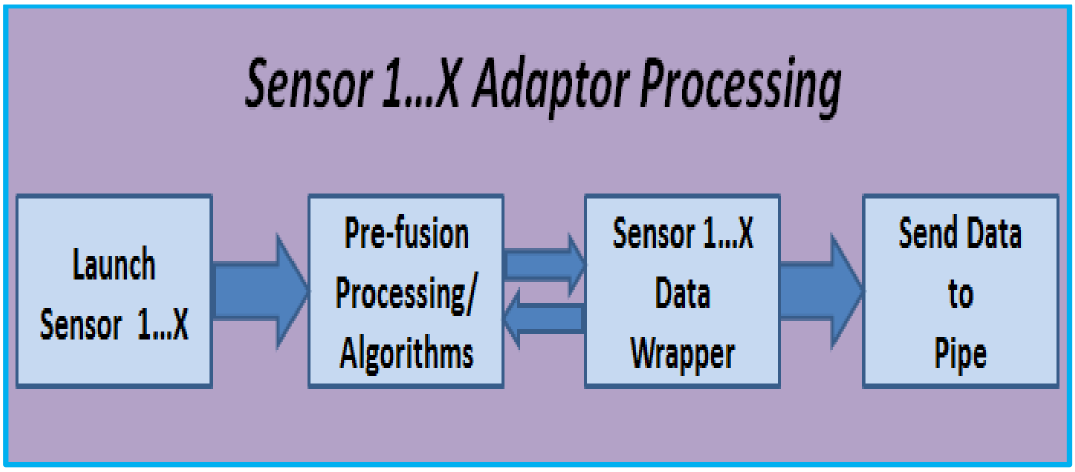



**Figure 3-15 Sensor X Adaptor Processing**

The Sensor X adaptor processing incorporates the following modules:

**Launch Sensor Module:** This activates a sensor for a specific AC related monitoring activity. Once Sensor X is correctly launched it is responsible for the capture and processing of its affective sensor related data.

**Pre-fusion Processing/Algorithms Module:** This module directly relates back to the previous discussion on how individual sensors are enabled with varying degrees of intelligence applied to the specific nature of the sensor and also in terms of affective analytics. For example, this may relate to embedded quality control functionality for internal device sensors or it may be applied affective reasoning capabilities on-board the sensory device itself. These sets of processes are unique to the individual Sensor X and may also be the subject of bespoke development where individual sensors (i.e. components of Sensor X) may be targeted within a device.

**Data Wrapper Module:** The data wrapper module is responsible for the packaging of the Sensor X data into an established common format for onwards communication back to the AC platform. The data wrapper services may be configured to only accept compilations of features or affective decisions under specific temporal constraints. The Sensor X data may also have to meet certain quality assurance/reliability standards and confidence levels before onwards processing and communications to the AC platform. Both the pre-fusion and data wrapper services are interrelated and responsible for processing trusted affective state data from Sensor X back to the platform. It is across these two modules that the very nature of the feature and decision fusion mechanisms can be implemented at the individual sensor level.

The discussion on the pre-fusion and data wrapper modules above are directly related to the S-Strata information model and will be discussed from a multi-fusion perspective later in this section. Also noted, and with reference to the S-Strata, the data wrapper service may not only process the affective feature data but may also provide other factual and contextual data relating to the contextual state, timestamps, confidence levels, evidence values, acquisition rates etc.

**Send Data Module:** Affective data produced by the data wrapper module may be a specific emotion classification for higher level decision based fusion or it may be a set of raw feature data to be used in onwards feature level fusion. Once the affective data is accepted and formatted by the data wrapper module, it is sent for onwards processing to the AC platform by the send data module which also handles any communications error and failure processing on behalf of Sensor X.

**Multi-Sensor Fusion Processing Framework:** The generic sensor adaptor processing discussed above in Figure 3-15 Sensor X Adaptor Processing is now applied to a framework that describes the lower level interface layers of a conceptualised AC platform with reference to the S-Strata information model.

Figure 3-16 Multi-Sensor Fusion Processing Framework illustrates wearables, vision, gait and speech sensory (Sensor X) adaptor interfaces and their associated storage and compute cloud related services. The Sensor Applied Processing stack on the right hand side of the figure refers to the individual Sensor X processing adaptors which represent a set of disparate processing modules depending on the types of AC sensing modalities engineered for the platform.

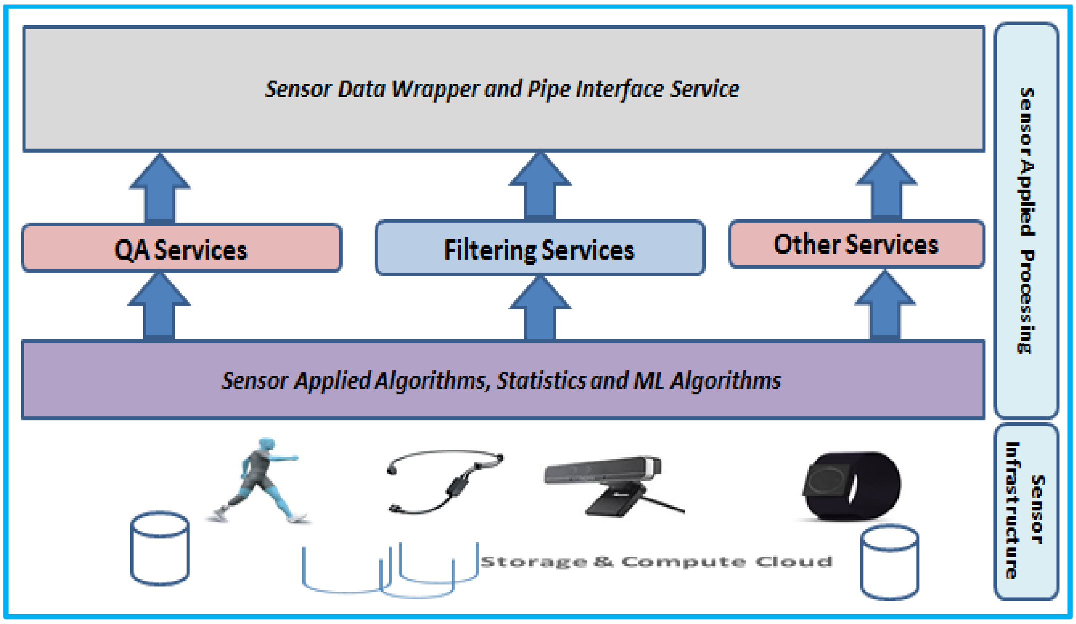



**Figure 3-16 Multi-Sensor Fusion Processing Framework**

In the middle of this stack are three modules named QA Services, Filtering Services and Other Services. With applied reference to the S-Strata, these modules identify with the coloured strata lines in the information model and primarily represent the computation of applied signal and affective intelligence services relating to individual sensors.

**QA Services:** The framework's QA module refers to the feature data quality control (FD-QC) stratum from S-Strata and provides for the development of a range of software services that control and manage the quality assurance (noise/interference) of the raw data from the various sensor components in the device used. The QA module can also provide services at an AC level (above the raw sensory data) and act as a control of the affective features and decision making capabilities of the device.

**Filtering Services:** With reference to the S-Strata, the feature data attributes (FDA), computed feature data (C-FD) and the internal feature relationship(s) (IFR) strata relate to the filtering services module in the framework. Generally speaking and with reference to the electronic sensory component level, filtering services may come pre-engineered as part of the device. This module highlights that there may be requirements for customised filter algorithms applied to the electronic signal data and it provisions for this scenario in the fusion processing framework.

The FDA, C-FD and the IFR strata can be expected to apply more to the filtering services at an affective processing level. Outside of the mandatory feature processing, certain emotion states may need to be filtered out of the AC analytics process on a subject. Such affective filtering algorithms may be facilitated via common knowledge; medical reasoning or the filtering may be based on personalisation profiles of the subject under affective analysis.

**Other Services:** The Other Services module of the framework primarily references the sensor context data (SCD) and internal feature relationship(s) (IFR) strata of the S-Strata model. This (Other Services) module represents scenarios where a specific Sensor X may be configured with a range of contextual data in relation to the affective tracking process. It may also provide low level internal feature data intelligence to the sensors in relation to the specific use case application domain context. For example in the case of a person with dementia (being monitored by an AC eHealth platform) the module may offer applied intelligence to the various sensors for key times during the day where various levels of sensory data are required. This may also lead to deeper personalisation and informed analytics, where the sensors can become smarter with access to more intimate knowledge and understanding of the subject under affective monitoring.

Generally, the multi-sensory processing framework described above provisions for each sensor having its own set of unique services modules (QA, Filtering, Other) and it is only when higher level feature, decision or hybrid level fusion processing occurs do the real multi-sensory issues arise. The S-Strata model primarily accepts this premise but it uniquely provides for certain low level inter-sensory processing services in the form of the external feature relationship(s) EFR stratum.

The EFR stratum can provide for specific reasoning and processing services across a collection of similar/disparate sensors such that the confidence levels may be increased in the affective classification data. For example platforms may have multiple vision sensors and decisions may be required on the best frame image to submit for classification. Similarly, in situations where occlusion occurs for a vision sensor its software stack may need to call on the services of other sensors to assist it with supporting evidence for a critical vision based affective evaluation.

This section presented a conceptual framework for AC sensory fusion. The discussion on adaptor processing focused at an individual sensor level and presented a conceptual overview of the spread and types of processing to be carried out. The subsequent low level fusion processing framework demonstrated sensory fusion at the adaptor layer and then applied the conceptual S-Strata information model in a more practical context and demonstrated how its various strata elements directly relate and apply across the modules of the multi-sensor fusion processing framework.

## 3.4 Design of Conceptual Architecture

The previous section discussed a framework for sensory processing at the lower layers of a conceptual AC platform. This section builds on these lower layers and presents a design for the overall conceptualised architecture of an AC multi-sensory fusion platform.

### 3.4.1 Affective Computing Platform Conceptual Architecture

For the purpose of this section, the concept of a **Pipe** will generally refer to a software communication bus which acts as an interface between the various sensor adaptors (discussed in the previous section) and the AC platform architecture. The additional modules represented in Figure 3-17 Affective Computing Platform Conceptual Architecture are introduced and explained below. The figure combines a number of services layers under a stack called AC Fusion Services shown on the right hand side. Each of these layers are discussed below with reference to the AC-Strata information model introduced earlier in this chapter.

The AC-Strata incorporates the S-Strata information model and provides for multiple sensory processing at varying time intervals. The SS strata processing denoted by the symbols in the AC-Strata figure directly reference the Pipe Server Interface Service and the Multi-Sensor Fusion Wrapper Services modules in the conceptualised architecture.

**Pipe Server Interface Service:** This service module is responsible for launching the individual modality sensors and maintaining the communication process with each sensor. Compiled affective data streams from the various sensors are reported back from the wrapper services to the AC platform via the pipe server interface service.

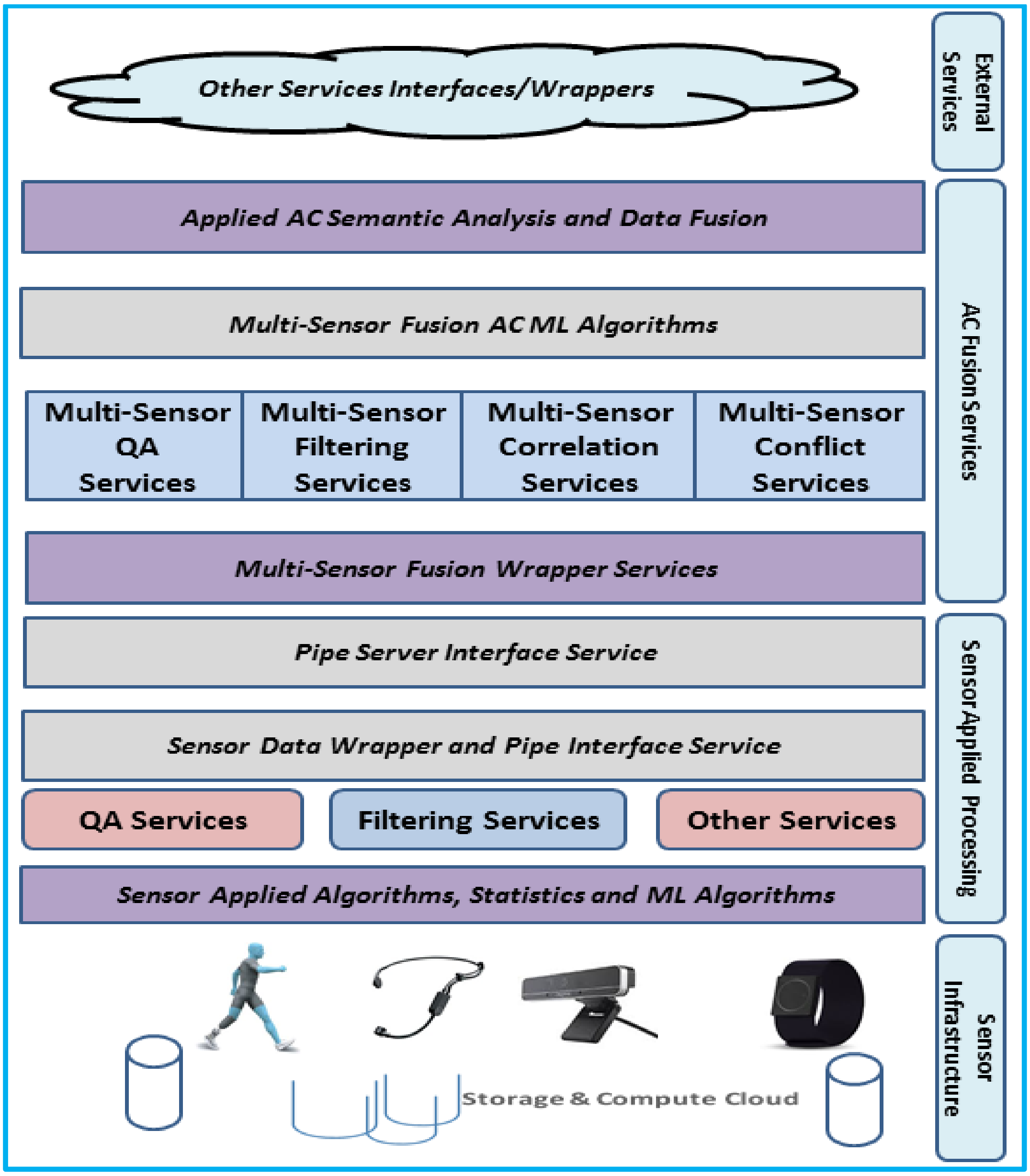



**Figure 3-17 Affective Computing Platform Conceptual Architecture**

**Multi-Sensor Fusion Wrapper Services:** This module is used to manage a range of sensor services such as quality assurance, filtering, correlation and conflict issues. While similar services have been discussed in the previous section, the justification for this layer is in relation to its role in the management and coordination of the sensors at the multi-modal, multi-sensory fusion contextual level. Each of the individual services managed and coordinated by this layer are discussed below.

**Multi-Sensor QA Services:** Sensory affective data at this level has already passed lower-level individual sensor quality assurance. This suite of services represents the SS feature data quality control (SS-QC) stratum in the AC-Strata. The quality control relates to multi-sensor evaluation aspects which may involve trusting one sensor modality over another or selecting or rejecting data when you may have multiple sensors for one modality such as vision. Here the focus is primarily about contributing to the compilation of the most relevant and quality assured data for the fusion processing in the AC ML algorithms module.

**Multi-Sensor Filtering Services:** This has already been discussed as part of the individual processing framework. This set of services primarily reflects the SS-C context stratum from the AC-Strata model. Similar processing is conceptualised to that carried out at the lower sensor level but the context here is the filtering of AC data streams with more applied reference to the use case domain. This may incorporate the reduction of the individual sensor feature vectors thus reducing complexity for onwards decision and feature level fusion schemes.

**Multi-Sensor Correlation Services:** This suite of algorithms focuses on cross sensor analysis to seek out correlation evidence to support more informed affective decision making for use in the AC and ML algorithms module. The services here associate directly with the SS computed features (SS-C-FD) stratum of the AC-Strata and typical services may involve feature analysis techniques, further feature reduction or processing of new features to add value for onwards processing in the architecture. The objective here is to offer applied services that can increase the confidence levels in the sensory data streams coming from the lower level sensor layers.

**Multi-Sensor Conflict Services:** The SS-C context data strata and the SS-A attributes strata from the AC-Strata model are of relevance to this suite of services. The aim of the multi-sensor conflict services is to handle sensors reporting conflicting emotional state data as a first pass before applied fusion processing in the algorithms module. It is conceptualised that the services here provide affective intelligence that may be a lot more applied and contextualised to the application domain environment. The services typically play the role of gatekeeper and can be used to facilitate informed decision making where sensor conflicts exist for either the same or disparate modalities.

**Multi-Sensor Fusion AC ML Algorithms:** With reference to the AC-Strata all of the coloured strata also apply to this module. This module is engineered to support the multi-sensor fusion scheme which may be at the feature level, decision level or a combination of both into a hybrid fusion scheme. Both generic and bespoke AC statistical techniques, algorithms, and machine learning processes are engineered for the platform in relation to the application domain use case scenario. This multi-sensor fusion processing module can also incorporate voting, probabilistic, and statistical methods and techniques in the affective decision making related to the selected fusion scheme.

**Applied AC Semantic Analysis and Data Fusion:** At this level, the affective analytics decision(s) from the previous AC and ML algorithms module enter a semantic analytical and data fusion process. This can involve semantic and ontological affective reasoning specifically relating to the use case domain and also to the personalisation features of the subject under observation. This module caters for unique semantic and ontological aspects and this is where specific domain related affective intelligence may be applied and engineered into the AC platform.

**Other Services Interfaces/Wrappers:** This module exposes the affective data services such as database stream management systems (DSMS) (Chatziantoniou & Doukidis, 2009), patient lifecycle management systems (Kowohl, et al., 2016), cloud/API interfaces and platforms similar to SenseCare (Bond, et al., 2017) for AC related eHealth application services.

### 3.5 Chapter Summary

This chapter on conceptual modelling and design presented typical use cases for an AC platform in an eHealth context. The specific functional and non-functional requirements of an AC platform were also presented and explained.

Prior to the conceptualisation of the platform architecture, the stratification concept, originally applied to multimedia, was used to create two conceptual information models, namely the S-Strata and the AC-Strata. These two stratification models were also linked conceptually with the Dasarathy data fusion model presented in chapter two. Low level data stream discussions were also provided in relation to vision and physiological sensory modalities from an information modelling viewpoint.

The S-Strata information model was then developed and expanded on by means of a processing framework that incorporated single sensors (S-Strata) reporting into a multi-sensor unification process. The S-Strata and the related multi-sensor processing framework were then presented in the context of the higher-level AC-Strata information model. The AC-Strata (incorporating the underlying S-Strata) was then further developed and applied to the overall conceptualised architecture of a proposed multi-sensory fusion AC platform.

While the grand scale of the conceptualised architecture for multi-sensory fusion proposed in this chapter is well beyond the scope of this thesis, certain elements of the architecture have been applied to the development of specific prototypical artifacts that were used for the remainder of the thesis research and the AC experimental phases. These specific artifacts are now introduced and explained in the next chapter.

# 4 Proof of Concept and Implementation

This chapter presents the engineering, development and implementation of an AC prototypical software and hardware solution that is based on the conceptual architecture that was formalised in chapter three. The first section (4.1) applies the conceptual architecture from chapter three and presents a prototypical solution that has been developed and used throughout the AC experimental phases of the research. It also discusses the higher layers of the solution's software artifacts and how they link with the conceptual architecture and theoretical stratification models.

The next two sections (4.2 and 4.3) move deeper into the conceptual architecture and present both vision and wearable adaptors that have been developed to interface with the prototypical solution. Both of these sections refer back to the stratification models and processing framework discussed previously. They will explain how the models and framework are conceptually related to the design and code base for each of the actual sensor adaptor software artifacts that were engineered and developed. The fourth section (4.4) outlines two other sensor adaptors that were developed for the prototypical solution. It also documents other investigatory research into future adaptor potentials.

For summary purposes, the fifth section (4.5) presents a review of the prototypical software architecture with further discussion around related technical themes. It concludes with insights into future developments in relation to the prototypical software platform. The final section six (4.6) is provided specifically for the reader, it acts as a major milestone in the thesis document and provides an overall summary of the research journey this far, before advancing to the next chapter five on AC experimental evaluation.

## 4.1 Conceptual Architecture: Prototypical Solution

This section presents a prototypical solution that has been conceived, formalised, engineered, and developed using both the stratification models and the AC conceptual architecture of chapter three. The first part presents a general overview of the current iteration of the prototypical solution that has been developed and includes discussion on the multi-sensor architecture and the concept of a sensor generic adaptor. Microsoft Pipe Server technology is a core communications component of the prototypical solution and is presented in the second part of this section. The final part presents a software oriented technical insight into the prototypical solution architecture and its related code base.

### 4.1.1 Prototypical Solution: General Overview

During the early stages of this research, both academic and practical work was carried out in relation to various sensor modalities with AC potentials. As a direct result of this multi-sensor oriented research and with reference to the stratification and conceptual models, a prototypical solution to be referred to as the Emotion Fusion Server (EFS) was developed.

**General overview of EFS:** The Figure 4-1 Prototypical Solution - EFS Overview presents a general overview of the EFS from a multi-sensor fusion perspective. The left hand side of the diagram represents four typical sensors that provide for vision, wearables, PC inputs and brain computer interface (BCI) AC related feature data. The middle of the diagram represents applied sensor related algorithms and processing with the names of the clients in the diagram actually relating to the individual software artifacts that were developed for each sensor. The output AC related data streams from the four sensor clients represented in the diagram are then submitted to the EFS for fusion and AC related analytical processing.

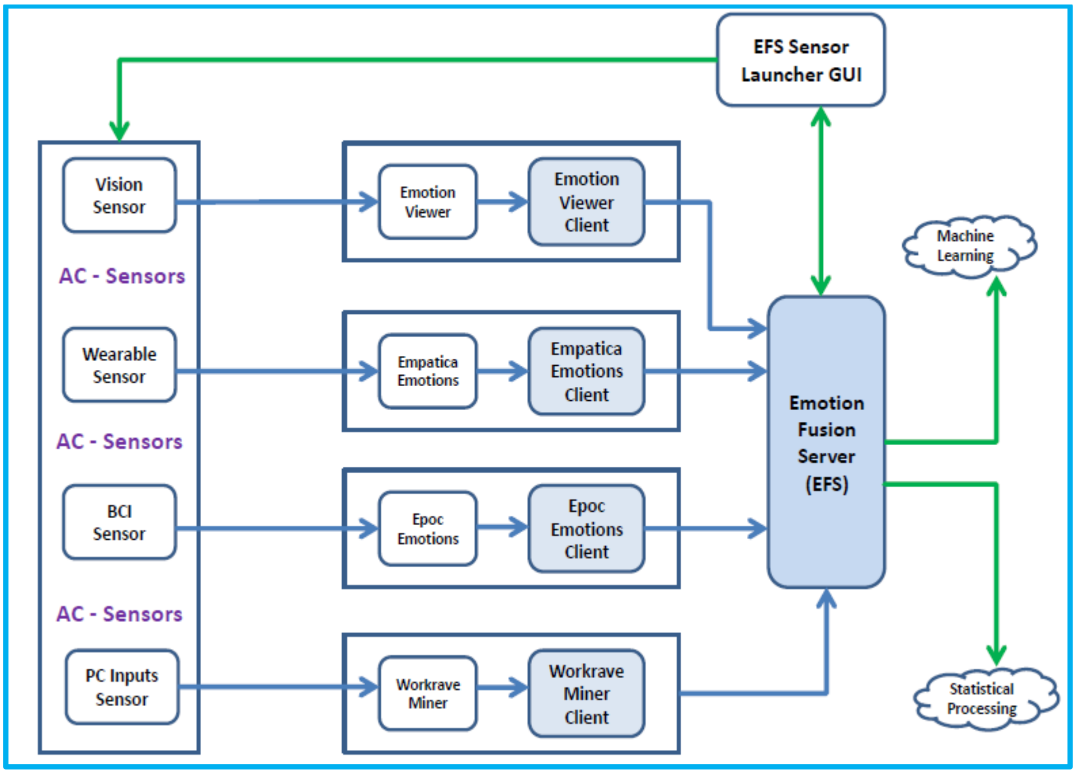



**Figure 4-1 Prototypical Solution - EFS Overview**

**Multi-sensory architecture of the EFS:** The Figure 4-2 Prototypical Solution EFS Processing Framework Overview presents a high-level technical representation of the typical processing pipeline of the EFS.

The top row of the framework relates to the individual sensors integrated into the EFS. Following the diagram flow above, the sensor processing functionality represented (reference numbers one (1) to six (6)) directly relates to various aspects of the S-Strata stratification model and the multi-sensor fusion processing framework already discussed in chapter three. This will be discussed later with reference to the EFS sensor generic adaptor.

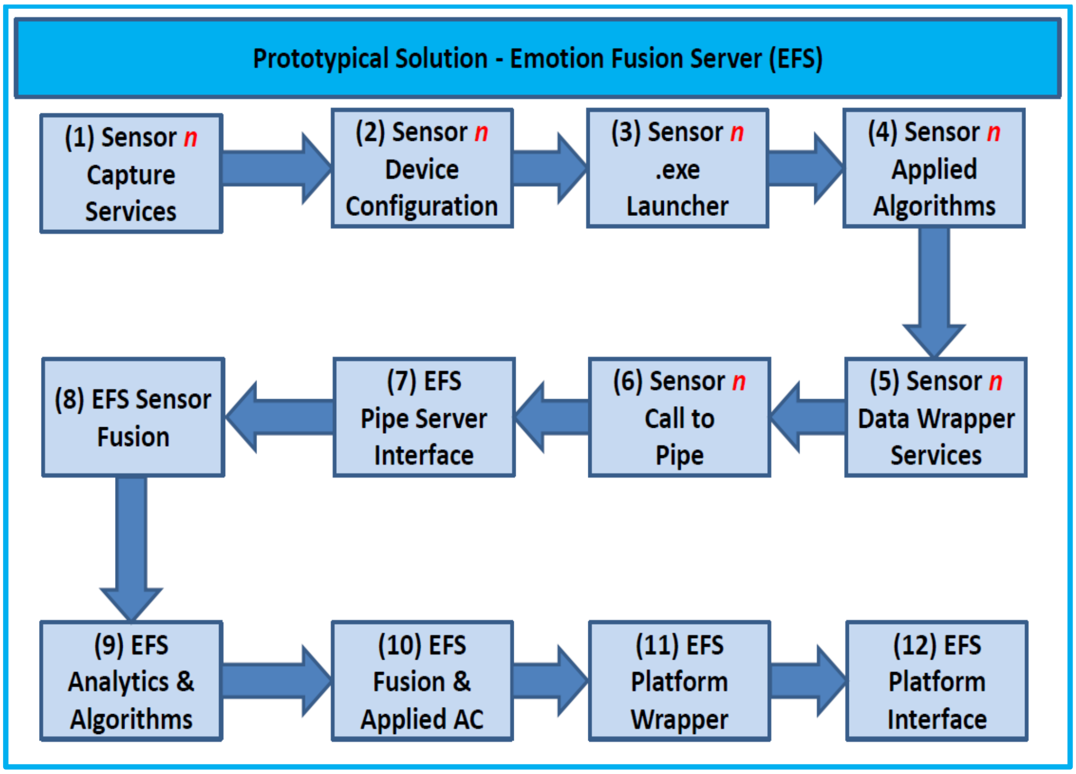



**Figure 4-2 Prototypical Solution EFS Processing Framework Overview**

Picking up the flow of the processing framework diagram above (from number seven (7) onwards), the remaining functionality incorporates the fusion of the AC feature data from the various sensor modalities, implementation of related fusion schemes and higher level domain related applied AC algorithms and techniques. The processing framework functionality represented in the diagram from number seven onwards directly relates to the AC-Strata and involves multi-sensory fusion and a number of advanced sensory feature processing requirements (represented by the coloured lines in the AC-Strata) which can be developed and implemented across the EFS processing framework.

While the AC-Strata represents abstract thought processes in relation to the EFS prototypical solution, the Figure 3-17 Affective Computing Platform Conceptual Architecture and its top level AC Fusion Services stack discussions of chapter three conceptually explains the type of processing required after AC feature data is returned by the various sensors integrated with the EFS platform.

On a practical note, and with reference back to the above EFS processing framework diagram, the actual sensor AC feature data streams are communicated back via the EFS Pipe Server Interface (see seven (7) in the above diagram). The pipe server interface is an integral part of the EFS platform and will be discussed further in the next section.

The Figure 4-2 Prototypical Solution EFS Processing Framework Overview has been provided to introduce the more technical aspects of the EFS and to show how it directly relates to the two abstract stratification models, AC-Strata and S-Strata. The EFS framework can also be seen as a practical prototypical implementation of a number of the concepts presented in Figure 3-17 Affective Computing Platform Conceptual Architecture and discussed in section 3.4 Design of Conceptual Architecture.

Throughout this chapter various functionality of the EFS processing framework will be presented and explained in further technical detail with reference to practical software artifacts that were developed during the thesis research. With this in mind, the concept of a sensor generic adaptor is a fundamental aspect of the EFS platform engineering which is discussed next.

**EFS sensor generic adaptor:** The Figure 4-3 Prototypical Solution EFS Sensor Processing View is a simplified representation of the specific EFS sensor related processing functionality discussed in Figure 4-2 and with reference in process flow numbers (1) to (6). The sensor processing view is also presented with reference to the specific sensor adaptor processing discussions of chapter three. The top part of the diagram below explains how sensors must be configured, connected via the pipe server and then executed, while the bottom part provides for sensors reporting back via the pipe server for onwards EFS related fusion and analytics.

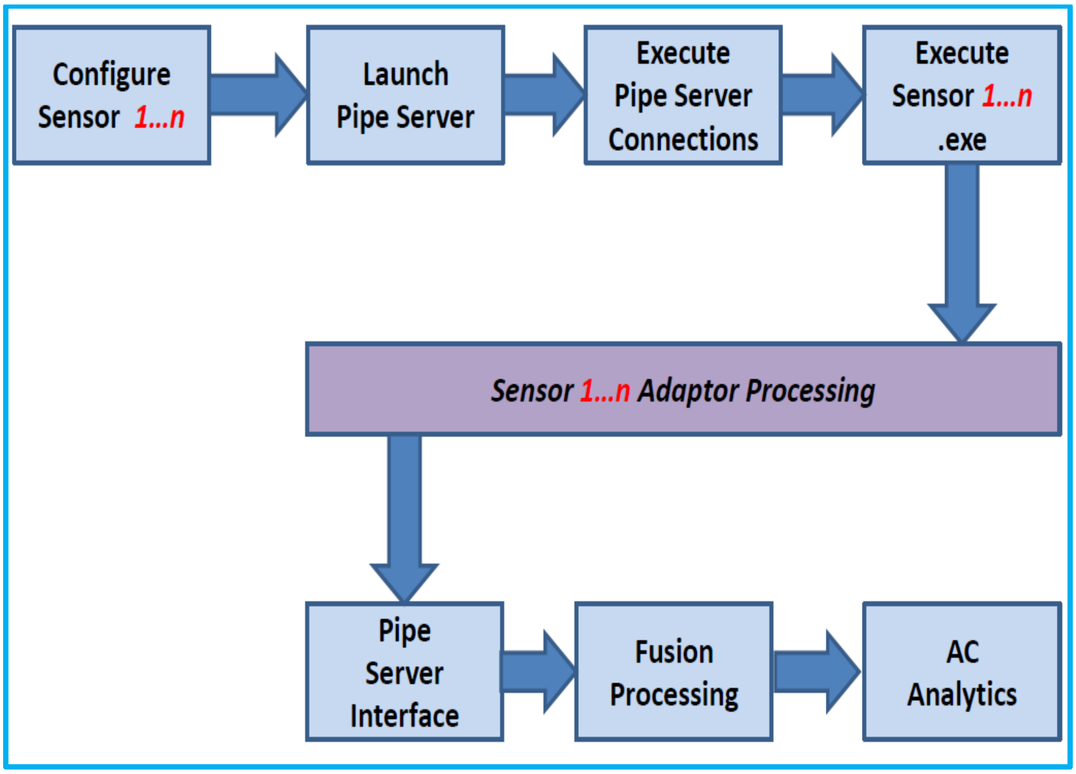



**Figure 4-3 Prototypical Solution EFS Sensor Processing View**

The middle section *Sensor 1…n Adaptor Processing* is where the various sensor processing is conducted and it is directly related to the conceptual discussions of chapter three in relation to the S-Strata. Sensor (*1…n*) adaptor processing is an integral part of the EFS platform. This is now further expanded upon below under what will be generally referred to as a ***Sensor Generic Adaptor***.

The Figure 4-4 Prototypical Solution EFS Sensor Generic Adaptor diagram presents a template for a typical sensor generic adaptor. Each sensor adaptor developed for the EFS is required to follow this template in terms of structure and processing flow/functionality. The sensor generic adaptor diagram describes standard sensor setup, pipe server communication and the actual launching of the sensor itself.

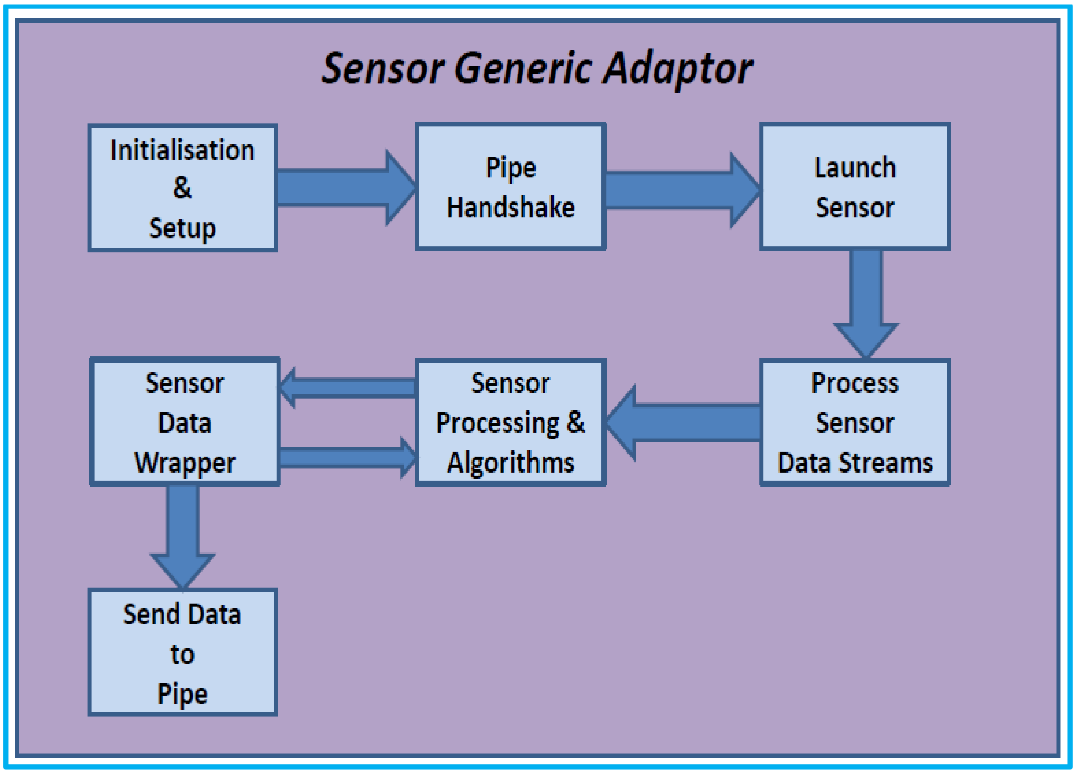



**Figure 4-4 Prototypical Solution EFS Sensor Generic Adaptor**

The two processes named **Process Sensor Data Streams** and **Sensor Processing & Algorithms** are where various aspects of the S-Strata model may be deployed as required. These two processes in a sensor adaptor may represent embedded engineering already implemented as part of a sensor's sub-sensory components and may be predominantly aimed at signal data quality control, speed, and environmental aspects. On the other hand, these two generic adaptor processes can provide for customised AC algorithms and processes to be implemented on a per sensor basis and could also provide for sensor based affective decision making. The remaining functionality in the generic adaptor involves wrapping up the AC data streams (once a pre-defined time period has elapsed) for transmission of a data structure onwards via the communication pipe back to the EFS for next stage fusion related processing.

The sensor generic adaptor template outlined above has been used in the creation of a number of customised sensor adaptors for the EFS platform. Both the vision and wearables adaptors will be discussed in detail in section two and three of this chapter, while two other adaptors developed will be discussed briefly in section four.

The aim of this section was to firstly provide a non-technical general overview of the EFS. After this explanation, the overall multi-sensory processing framework of the EFS was presented with reference to the stratification models and the conceptual architecture of chapter three. This was then followed up with a focused discussion around the sensor modality processing aspects of the EFS platform and the presentation of a technical framework for a sensor generic adaptor.

### 4.1.2 Prototypical Solution: Pipe Server

The Microsoft Pipe Server functionality has been used as a core component in the software development for the sensor adaptor communications with the EFS. The below provides a brief introduction to the pipe client/server technology.

Microsoft defines a pipe as a shared section of memory that is used for inter-process communication. The process that creates a pipe is known as the pipe server and the process that connects to the pipe is known as the pipe client.

The pipe can be conceptually viewed as having two ends. A one-way pipe allows a process at one-end to write to the pipe while the process at the other end is allowed to read from the pipe. There is also a two way pipe (duplex) that provides for unique processes to read and write from their own specifically allocated ends of the pipe.

Two types of pipes can exist, anonymous pipes and named pipes. The anonymous pipe is unnamed and is one-way. They require less overhead but have limited functionality and cannot be used for network communication purposes. Named pipes are formally named and can be one-way or duplex. Once a pipe is named, a number of instances may be created. Each instance of the named pipe *has its own buffers and handles, and provides a separate conduit for client/server communication* (Microsoft, 2017).

The pipe server refers to a process that creates a named pipe. The server-side function for instantiating a named pipe is CreateNamedPipe() and the function for accepting a connection is ConnectNamedPipe().

The pipe client refers to a process that connects to an instance of a named pipe. A client process connects to a named pipe by using the CreateFile() or CallNamedPipe() functions.

The Microsoft code for their multithreaded pipe server technology is available at this reference[12] (Microsoft, 2017) and has been adapted and integrated into the EFS platform. Various software components for both the sensory adaptors and the EFS platform incorporate multithreaded named pipe server related processes. Processes such as establishing the pipe, the pipe handshake and the transmission of sensor data streams via the pipe will be discussed throughout the remaining sections in this chapter.

### 4.1.3 Prototypical Solution: Technical Overview

This section presents a technical software oriented synopsis of the EFS using a number of flow diagrams that explain sensor execution, pipe server communications and data stream processing and fusion functionality.

[12] https://msdn.microsoft.com/en-us/library/windows/desktop/aa365588(v=vs.85).aspx

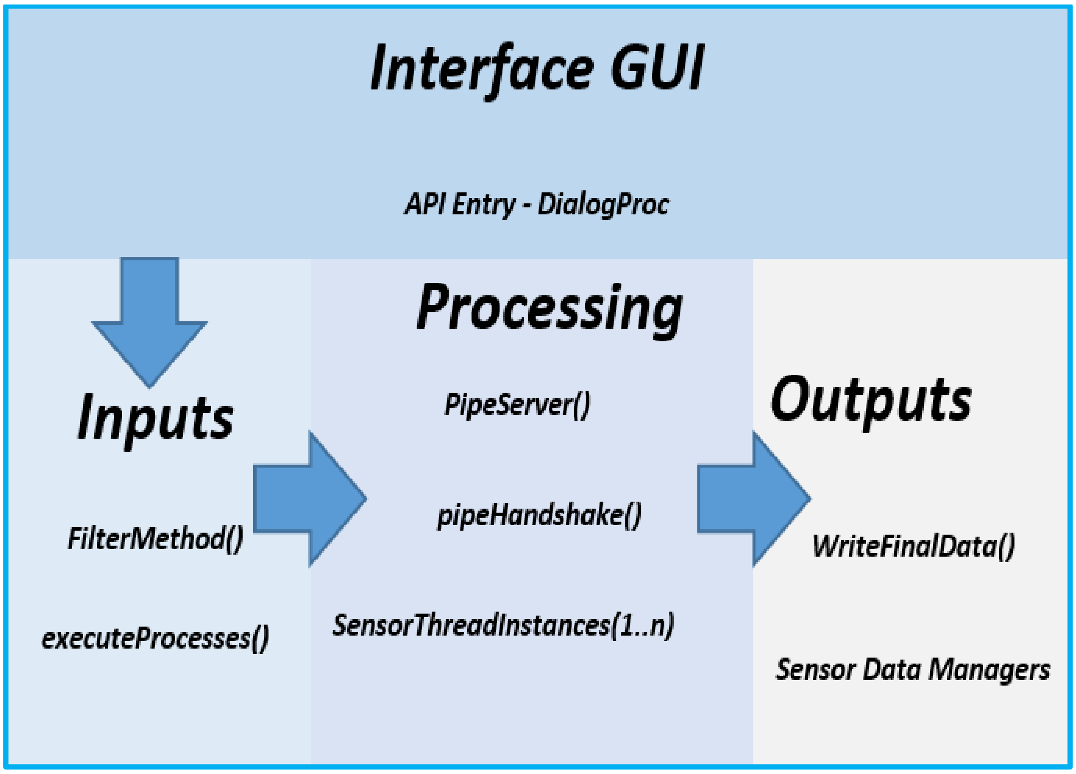



**Figure 4-5 Emotion Fusion Server (EFS) System Context Diagram**

The Figure 4-5 Emotion Fusion Server (EFS) System Context Diagram presents a high-level overview of the EFS interface, inputs, processing and outputs functionality. The EFS prototypical solution consists of a user interface for the selection and set-up of the various sensors to be activated for a monitoring session. This sensor selection process drives the system inputs which primarily call the FilterMethod() and executeProcesses() methods. The main sensor communication processing is managed by the PipeServer() and the pipeHandshake() processing methods. This functionality involves the management of multiple instances of communication threads for each sensor that has been activated for the AC monitoring session. The outputs represented relate to the individual sensors reporting back their time period defined data streams to the EFS using the pipe server. This functionality is enabled by a number of customised sensor data manager methods and the WriteFinalData() method.

The diagram and discussion above presented the various software components in the overall context of the EFS platform. The remainder of this section presents details on three of the main EFS software artifacts that were developed. Firstly the EmotionDataFusion artifact is discussed. This is then followed by a discussion on the Filter artifact (called from EmotionDataFusion) and finally the sensor data manager artifact is discussed.

**EmotionDataFusion flow diagram:** The Figure 4-6 EmotionDataFusion - Flow Diagram presents the graphical user interface (GUI) control loop for the EFS. This interface functionality is encapsulated in the API Entry, InitInstance() and the DialogProc() methods represented in the flow diagram. The EmotionDataFusion code base also provides for the main execution and processing of multi-sensor data streams using the FilterMethod() and executeProcesses() functionality.

The FilterMethod() is primarily involved in the pipe server communications and the sensor data stream management and processing and is explained separately below. The executeProcesses() method provides for the launching of each of the sensor adaptors integrated with the EFS platform. The terminateProcesses() method is used to efficiently shut down the EFS.

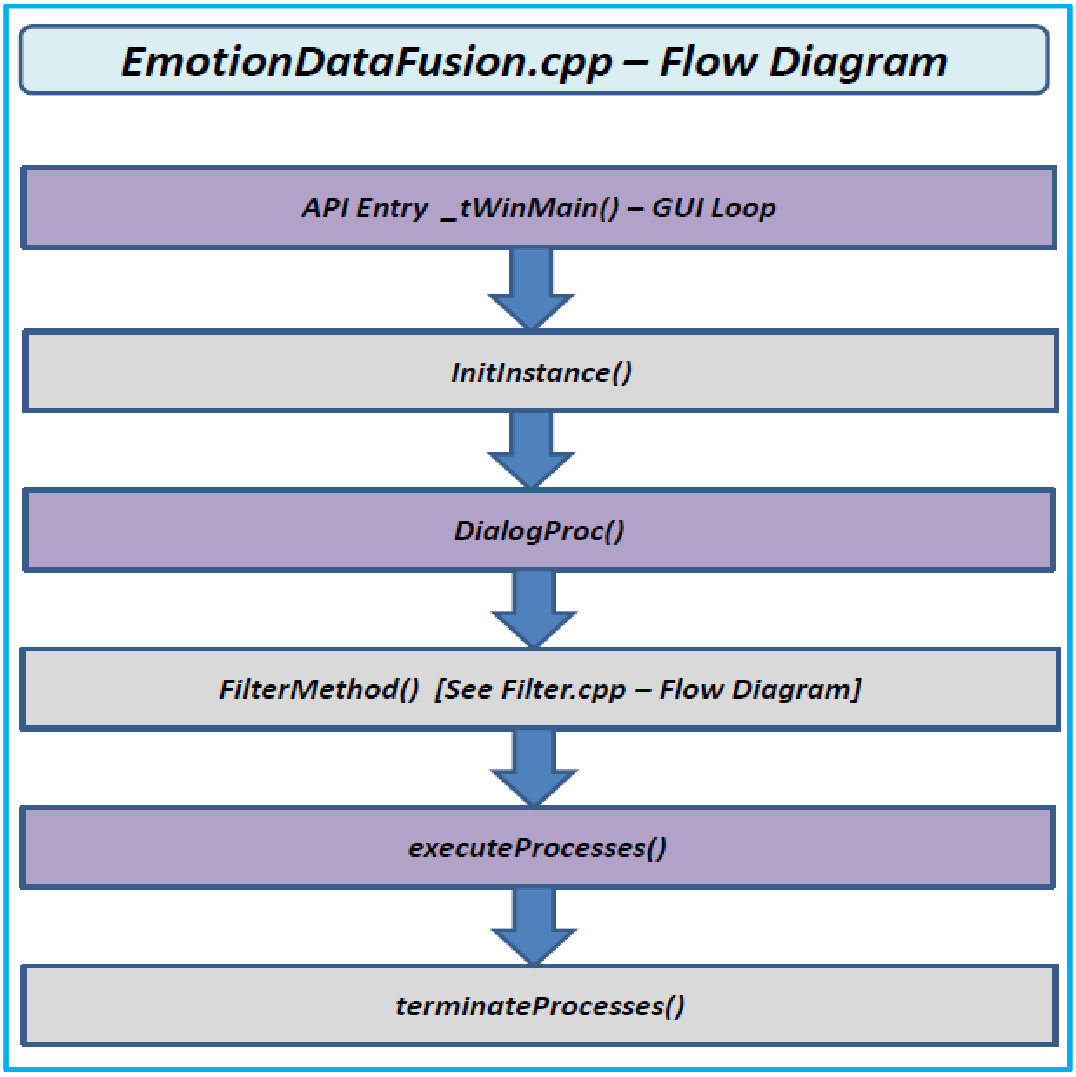



**Figure 4-6 EmotionDataFusion - Flow Diagram**

**Filter flow diagram:** The FilterMethod() in Figure 4-7 Filter - Flow Diagram is called from the EmotionDataFusion code and provides two main processing tracks. The left side demonstrates the PipeServer() setup and the pipeHandshake() methods for each of the sensors activated via the EFS GUI. Each sensor selected creates a unique instance thread which then activates the associated sensor data manager. This multi-sensor functionality is represented by *InstanceThread_Sensor1..n()* in the Filter flow diagram and involves novel code customisation to address each of the unique sensor adaptors integrated with the EFS platform.

The right side represents the data stream outputs from the various sensors communicated with via the sensor data mangers. The various sensor data streams are then fused together into a feature vector and saved using the writeToFileFilter() method.

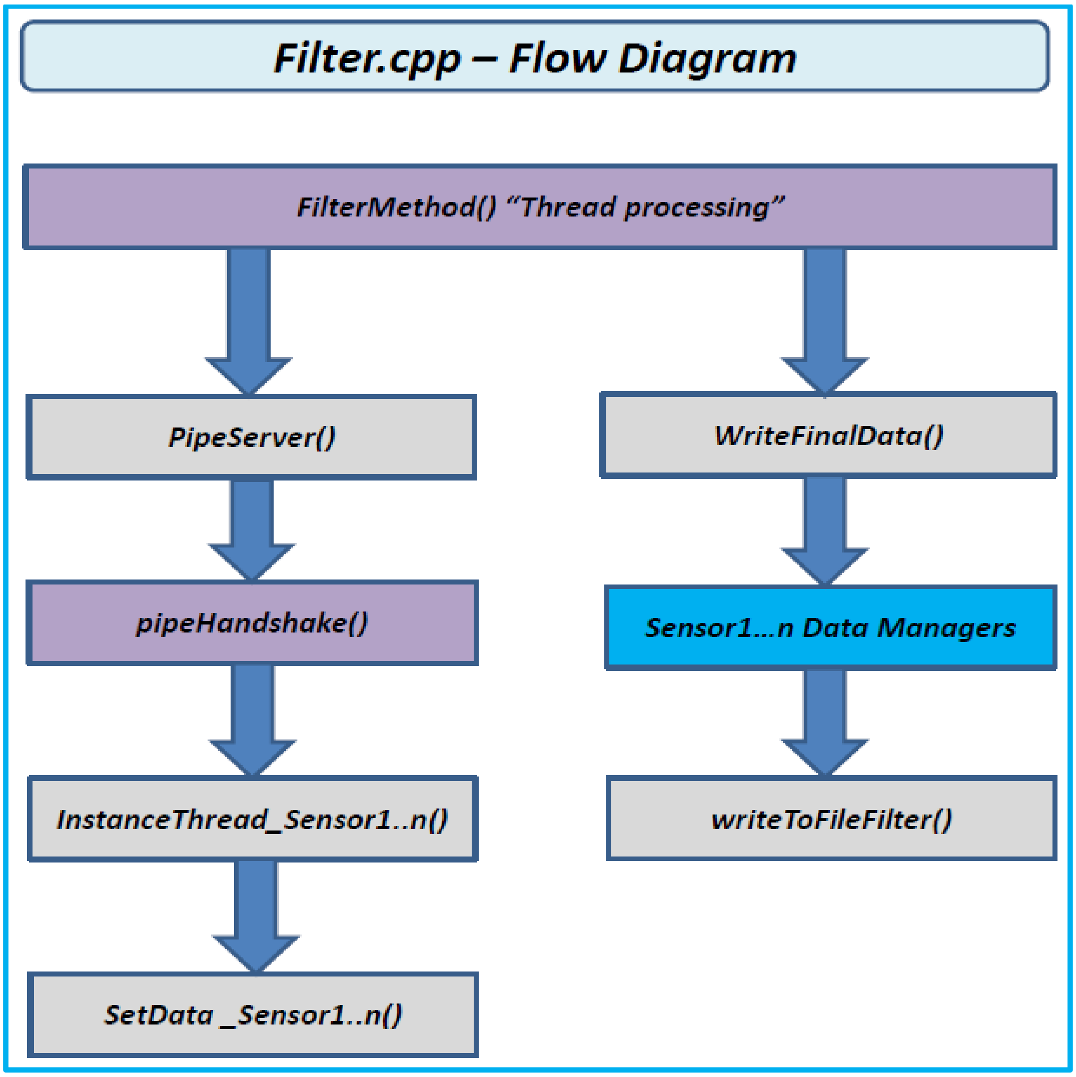



**Figure 4-7 Filter - Flow Diagram**

The Filter code base is engineered such that it can be expanded and developed to incorporate advanced feature, decision or hybrid sensory fusion schemes in the future. This is where many of the higher level AC functionality issues identified and discussed across chapter two and the conceptual modelling and design chapter three may be addressed from a fusion perspective.

As represented in the Filter flow diagram on the right hand side, each sensor adaptor has a unique sensor data manger which is presented and explained next.

**Sensor data manager flow diagram:** As described, each customised configured sensor data manager is activated from the Filter code base. Each sensor data manger is responsible for capturing the sensor data stream, formatting it for communication and for sending the data stream back to the EFS. The Figure 4-8 Sensor1...n Data Manager is a general representation of the functionality of a typical sensor data manager.

Each data manager performs sensor related initialisation along with the capture and processing of timestamp data. Once the sensor data is processed and compiled (generally based on a pre-determined time period) the sensor feature data is then converted into a string format and copied into a single sensor data stream string. The sensor data stream string is then provisioned for communication back to the EFS for further processing in conjunction with the other sensors and their reported data streams.

**Software artifacts extracts:** Selected software artifacts extracts relating to this section are provided in the appendices to this thesis in volume 2 of 2.

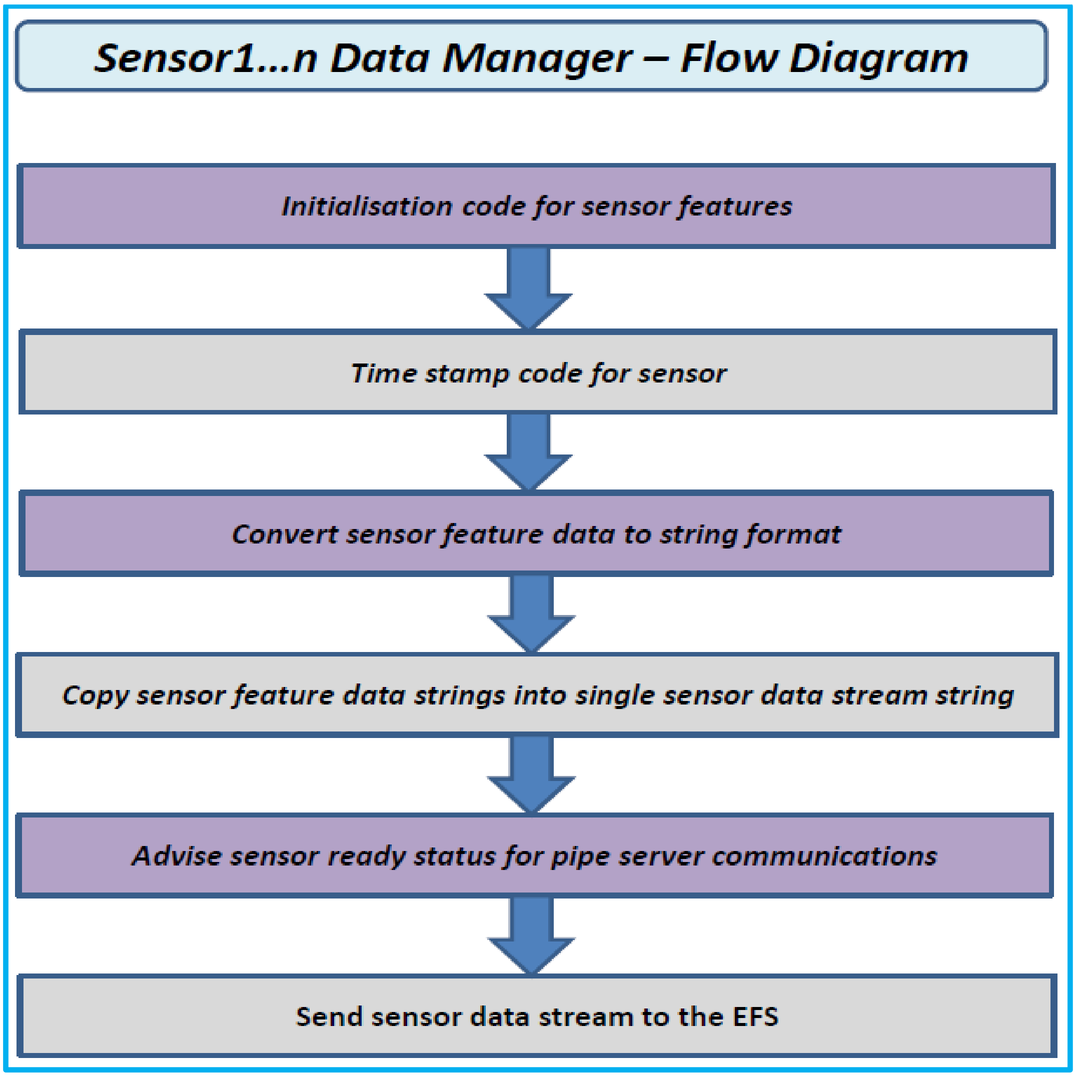



**Figure 4-8 Sensor1...n Data Manager**

### 4.1.4 Prototypical Solution Summary

This chapter section on the conceptual architecture of the AC platform prototypical solution opened with a non-technical overview of the EFS. This was then followed with a more technical discussion on the EFS processing framework.

A key component of the EFS is the functionality to deal with multi-modal sensory devices. This led to discussion on a core component of the EFS that is referred to as the sensor generic adaptor. The processing functionality of the sensor generic adaptor was them explained along with related flow diagrams.

Following this overview, the core software communication infrastructure underlying the EFS platform known as the pipe server was briefly explained. The final part presented a review of a number of core software artifacts that make up the EFS platform. The system context diagram was used to present the high-level interface, inputs, system processing, and outputs software methods of the EFS. In particular the EmotionDataFusion, Filter and the Sensor Data Manager artifacts were discussed and explained with reference to a number of flow diagrams.

## 4.2 Affective Computing Vision: Platform Adaptor Implementation

This section presents an overview of a vision adaptor developed for the EFS platform. This is followed by a discussion on underlying core technologies used as part of the adaptor development process. The logical software processing and functionality of the adaptor along with its related data manager is also provided.

### 4.2.1 Vision Adaptor Overview

The main vision adaptor developed for the EFS platform is to be referred to as the **EmotionViewer**. The EmotionViewer was developed using a developer edition of the Real Sense SDK (formerly Intel Perceptual Computing). The vision adaptor uses the Creative Senz3D Camera (Creative Labs, 2013) that was developed for the Real Sense SDK. Further technical details of the AC vision related components of the Real Sense SDK are discussed in the next sub-section.

The development of the EmotionViewer has incorporated AC related components that were licenced to Intel by Emotient as part of the overall Real Sense developer platform. The EmotionViewer adaptor primarily follows the sensor generic adaptor template discussed in the previous section. The EmotionViewer.cpp flow diagram in sub-section 4.2.3 explains how the adaptor currently functions and how it communicates with the EFS via the pipe server.

Once data has been captured and processed by the EmotionViewer adaptor, applied analytics and processing takes place. Based on pre-determined time constraints and adaptor connectivity, this will then periodically result in the EmotionViewer data streams being reported back to the EFS platform. These data streams are communicated to the EFS using the EmotionViewer data manager which is also discussed in section 4.2.3.

### 4.2.2 Vision Adaptor Core Technologies

This section introduces the Real Sense SDK and how it was used in the development of the EmotionViewer adaptor. It also discusses the SDK technical components that were applied and integrated and concludes with a non-technical overview of the Emotion Viewer adaptor algorithm.

The Intel® RealSense™ SDK (Intel, 2017) in Figure 4-9 Real Sense SDK Version 4 Architecture Overview is a library of pattern detection and recognition algorithm implementations exposed through standardised interfaces. The EmotionViewer adaptor has been developed using the SDK functionality of Intel Real Sense API version 4.0. The SDK library architecture, as illustrated in[13] consists of several layers of components. The core functionalities of the SDK are found in the input/output (I/O) and the algorithm modules. The I/O modules retrieve input from an input device or send output to a device. The algorithm modules provide various pattern detection and recognition algorithms for face, gesture and speech recognition, and text to speech (Intel, 2017).

[13] https://software.intel.com/sites/landingpage/realsense/camera-sdk/v1.1/documentation/html/index.html?doc_essential_programming_guide.html

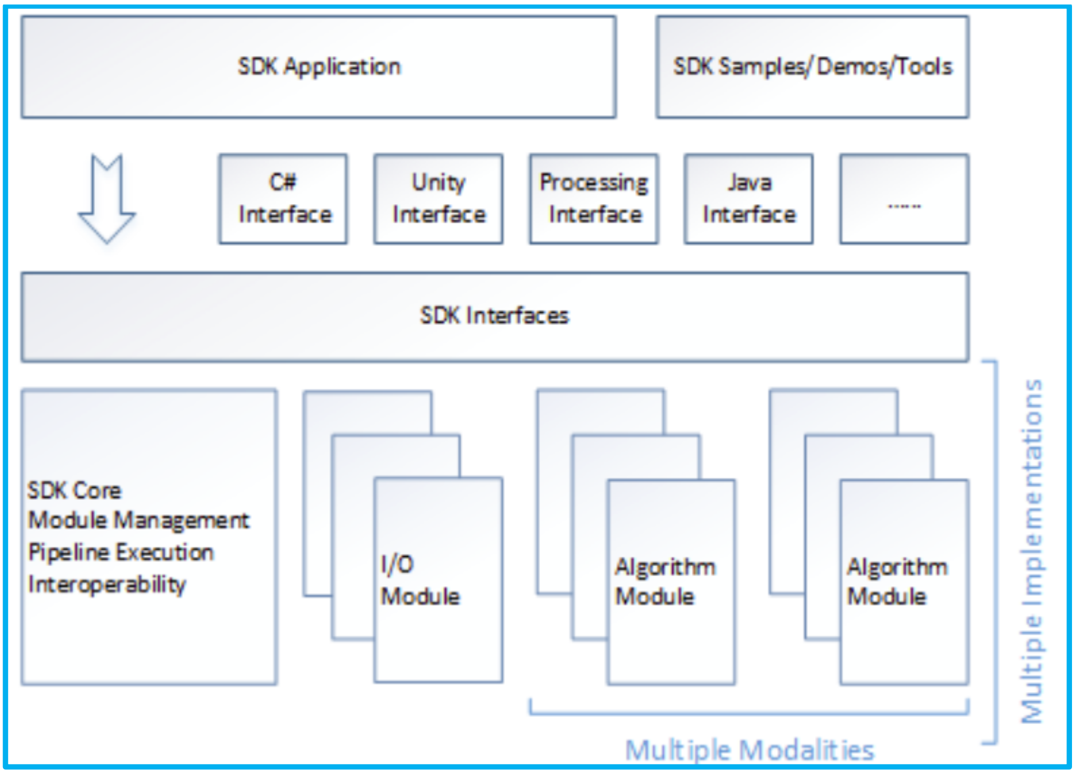



**Figure 4-9 Real Sense SDK Version 4 Architecture Overview (Intel, 2017)**

The EmotionViewer adaptor developed using the Real Sense SDK, estimates facial emotion states from still and video image sequences. The adaptor supports multiple emotion states and is capable of detecting affective states of anger, joy, fear, surprise, disgust, contempt and sadness from the vision frame data processed. The adaptor also provides general sentiment analysis such as positive, neutral and negative states relating to the identified emotions. Each emotion state also provides two scores for intensity and evidence that can be used to fine-tune the affective tracking of the EmotionViewer adaptor.

The Real Sense SDK 4.0 uses the following hardware and software setup:

- **Hardware requirements:** 4th generation Intel® Core™ processors based on the Intel microarchitecture, 8GB free hard disk space, Intel® RealSense™ Creative Senz3D camera (see Figure 4-10 Real Sense Depth Camera - Creative Senz3D )

- **Software requirements:**
    - Microsoft Windows 8.1 OS 64-bit or higher.
    - Microsoft Visual Studio 2010-2013 with the latest service pack.
    - Microsoft .NET 4.0 Framework for C# development.
    - Java JDK 1.7.0_11 or higher for Java development.

Real Sense is an evolving platform and the most current documentation can be found at the following reference (Intel, 2017).


**Figure 4-10 Real Sense Depth Camera - Creative Senz3D (Intel, 2017)**

The basic code containing the Real Sense emotion processing algorithms were separated out as part of the development of the EmotionViewer adaptor. This involved extracting and testing various sample code and the creation of a number of EFS related demonstrator applications. AC related features of the underlying emotion algorithms were also incorporated.

The development of the EmotionViewer has included support for facial expressions detection in a vision data frame, temporal processing and reasoning, data steam handling features, and emotional data compilation and analytics.

The following is a high level overview of the algorithm that has been implemented in the current version of the EmotionViewer adaptor.

- Set a defined time period for emotion tracking on a subject.
- Find and track the subject's facial expression from the Real Sense camera frame data delivered to the EmotionViewer adaptor.
- Use intensity and evidence values to decide if emotional states are sufficiently identified in the camera frame data.
- Perform computations and analytics of the AC data streams for the defined time period.
- Decide on the most prominent emotion for the defined time period.
- Write emotion state data to communication pipeline and also to a local file/database system.

### 4.2.3 Vision Adaptor Software Development

This section provides a technical insight into the EmotionViewer vision adaptor that was developed using the Real Sense SDK for the EFS platform. Figure 4-11 EmotionViewer - Flow Diagram explains the flow of the adaptor processing logic that closely follows the generic adaptor template previously discussed.

**EmotionViewer sensor adaptor:** The EmotionViewer adaptor code provides AC vision sensing capabilities to the EFS platform. After setup and initialisation the vision camera is launched using the underlying classes and methods of the RealSense SDK. The adaptor is responsible for the pipe server handshake process with the EFS and it also sets up default values for emotion data streams.

The QueryEmotion() method returns classified emotion related data that has been identified in the camera vision frame data. This emotion data is then used as input to the EmotionViewer vision analytics processes. The vision analytics involves processing both evidence, intensity and sentiment values returned in the QueryEmotion() data structure. One of the main objectives of the setAverageEmotion() method is to find the most dominant emotion identified in the vision frame data for the defined emotion tracking period which can be any pre-determined number of seconds.

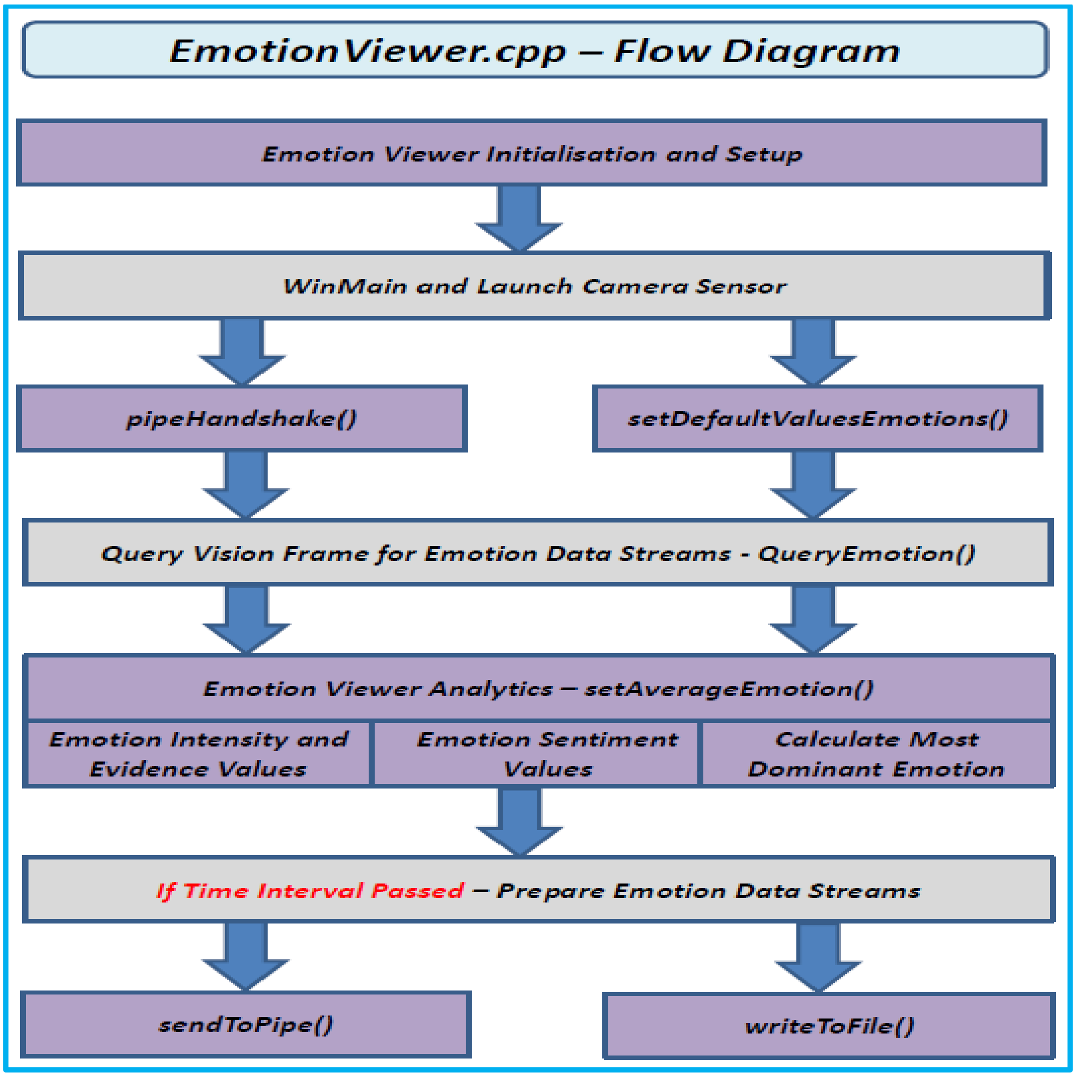



**Figure 4-11 EmotionViewer - Flow Diagram**

Once the vision tracking time period has elapsed, the results of the analytics processes are formatted into a data stream for transmission using the sendToPipe() method. The formatted vision data stream can also be written out to a secondary file/database if required, for individual vision sensor analytics at a later stage.

**EmotionViewer data manager:** The EmotionViewer data manager represented in Figure 4-12 EmotionViewer Data Manager - Flow Diagram primarily follows the data manager diagram outlined previously in Figure 4-8 Sensor1...n Data Manager. The data manager is responsible for formatting and preparing the EmotionViewer vision data streams received via the pipe server for final processing by the EFS as referenced in relation to the Filter code base discussed in the previous section and in Figure 4-7 Filter - Flow Diagram. The flow diagram is self-explanatory and provides the names of the methods used in the EmotionViewer data manager.

**Software artifacts extracts:** Selected software artifacts extracts relating to this section are provided in the appendices to this thesis in volume 2 of 2.

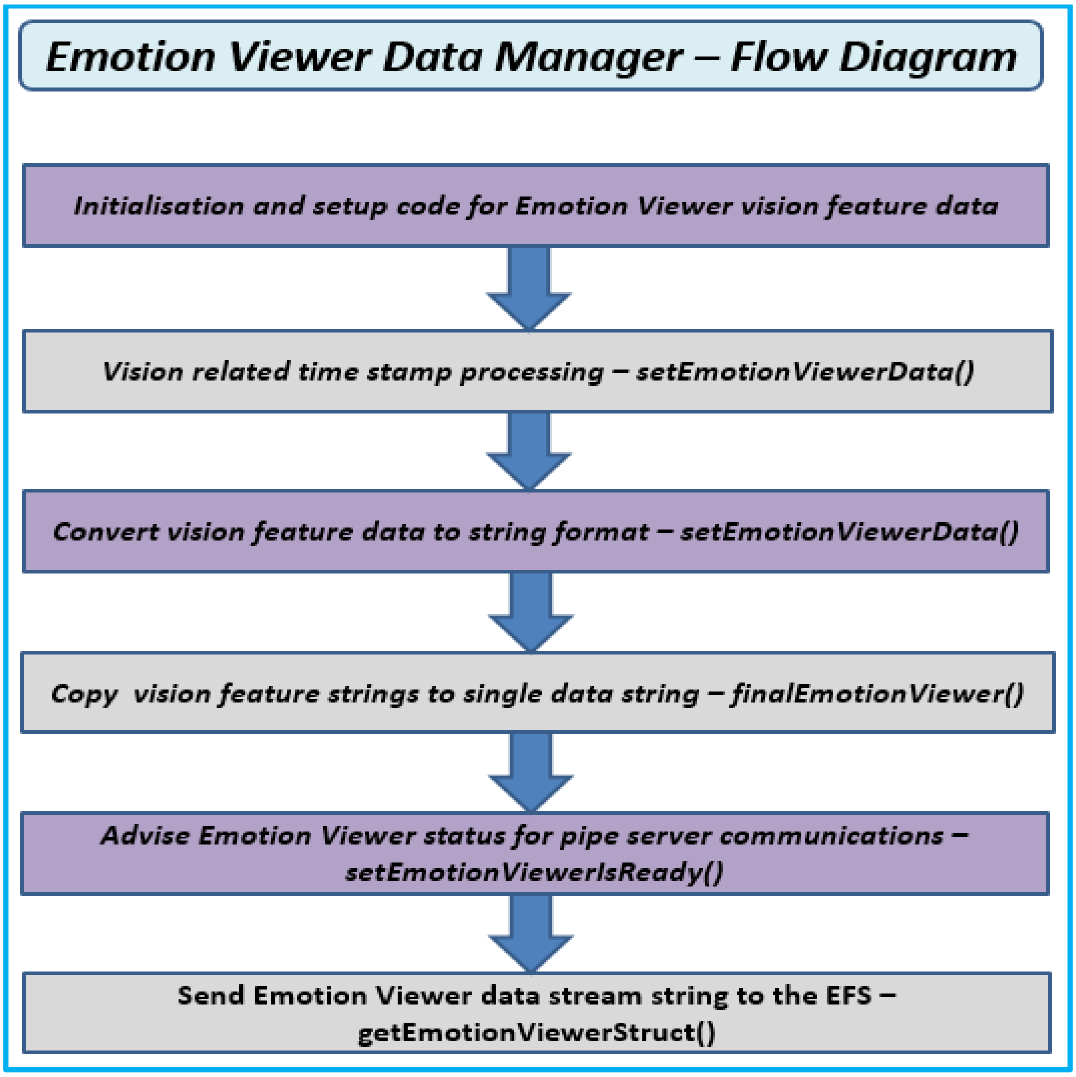



**Figure 4-12 EmotionViewer Data Manager - Flow Diagram**

## 4.3 Affective Computing Wearables: Platform Adaptor Implementation

This section presents an overview of a wearables adaptor developed for the EFS platform. This is followed by a discussion on underlying core technologies used as part of the adaptor development phase. The logical software processing and functionality of the adaptor along with its related data manager is discussed in the final section.

### 4.3.1 Wearables Adaptor Overview

The main wearables adaptor developed for the EFS platform is to be referred to as EmpaticaEmotions. The EmpaticaEmotions adaptor was developed using the Empatica E4 wearable device. The development of the EmpaticaEmotions adaptor has incorporated a number of software components released by Empatica for their E4 device. The current version of the wearables EFS adaptor has developed customised code to interface with the E4 Bluetooth connected client device and the Empatica E4 server. Details of these underlying software components and further technical details on the E4 are provided in section 4.3.2.

The EmpaticaEmotions.cpp flow diagram in sub-section 4.3.3 explains how the adaptor currently functions and how it communicates with the EFS via the pipe server.

Physiological data captured by the E4 wearable sensor is processed by the EmpaticaEmotions adaptor. Based on pre-determined time constraints and adaptor connectivity, this will periodically result in the E4 processed data streams being reported back to the EFS platform. This communication process involves the customised EmpaticaEmotions data manager which is explained using a flow diagram in sub-section 4.3.3.

### 4.3.2 Wearables Adaptor Core Technologies

This section introduces the Empatica E4 technology and how it was used in the development of the EmpaticaEmotions wearables adaptor. It also discusses the technical components that were applied and integrated and concludes with a non-technical overview of the adaptor algorithm.

The Empatica E4 wearable wireless device has been discussed already in both chapters two and three but as a reminder the E4 contains four sensors for PPG, GSR/EDA, an accelerometer and an infrared thermopile for reading skin temperature. The E4 operates either in streaming mode for real-time data viewing on a mobile device using Bluetooth® or in recording mode using its internal memory.

Empatica provides software tools such that E4 data can be transferred securely and easily to other devices. The following software services are available to developers from Empatica.

- **Empatica Connect** is a cloud based Web application for storing, viewing, and managing E4 data. The application can be accessed from any platform using a web browser.
- **Empatica Real-time** is a mobile App that provides wireless streaming and visualization of real-time E4 data on Bluetooth Smart Ready mobile devices.
- **Empatica Manager** is a desktop application for transferring data from the E4 and uploading it securely to the Empatica Connect cloud.

The E4 Empatica Connect dashboard provides access to user session details by time series for each sensor signal type available (GSR/EDA, HR, Temperature and Accelerometer) with event mark tags overlaid on the data views. Raw session data can also be downloaded in CSV format for easy processing and analysis in customised applications. E4 data is secured with encryption and can be deleted after use if required. The E4 Web dashboard can be accessed via secure login to an Empatica Connect account at this link[14]. The Empatica E4 is an evolving wearable device and platform, the most current documentation can be found at the following link[15].

As part of the software development process, each E4 device has to be uniquely registered on the Empatica Connect cloud service. A unique purchase registration key is required in order to authenticate each E4 device for access to session data sensor streams. Once an Empatica device is registered on the Connect cloud, session data can be uploaded and viewed for the device being worked on.

The EmpaticaEmotions adaptor engineering has involved code development to allow access to E4 sensor data streams directly from the device at a local level. This code development required a specific Bluetooth dongle in order to connect with and capture the E4 sensor data. The EmpaticaEmotions adaptor currently provides functionality for the production of pre-determined time period based data streams provisioned by the E4 device. The EFS EmpaticaEmotions adaptor has been developed and embedded with underlying client/server software components provided by Empatica that enable sensor communication interactions with the E4 wearable device.

[14] https://www.empatica.com/connect/
[15] https://www.empatica.com/e4-wristband

The following is a high level overview of the algorithm that has been implemented in the current version of the EmpaticaEmotions adaptor.

- Connect the E4 for local device access.
- Conduct interface processing for the connection of the E4 device with the EmpaticaEmotions adaptor.
- Compile and process E4 sensory feature data streams as specified for the EFS platform.
- Write E4 sensor data streams to communication pipeline and also to a local file/database system.

### 4.3.3 Wearables Adaptor Software Development

This section provides a technical insight into the EmpaticaEmotions wearable adaptor that was developed for the Empatica E4 device. Figure 4-13 EmpaticaEmotions - Flow Diagram explains the flow of the E4 adaptor processing logic that generally follows the sensor generic adaptor template.

**EmpaticaEmotions sensor adaptor:** Following EmpaticaEmotions initialisation and setup processing the executeEmpatica() method is called which launches the connectivity with the E4 wearable sensor. As the E4 sensor is connecting with the EmpaticaEmotions adaptor, the pipeHandshake() method is also in progress in order to create the adaptor connection with the EFS pipe server.

Once all connections are successfully established, the readSecondActivity() method starts the reading and processing of the E4 data streams. Currently the EmpaticaEmotions adaptor works by reading from a dedicated file that the E4 directly populates using its Bluetooth connection and direct client/server transmission control protocol (TCP) (TechTarget, 2017) device instructions.

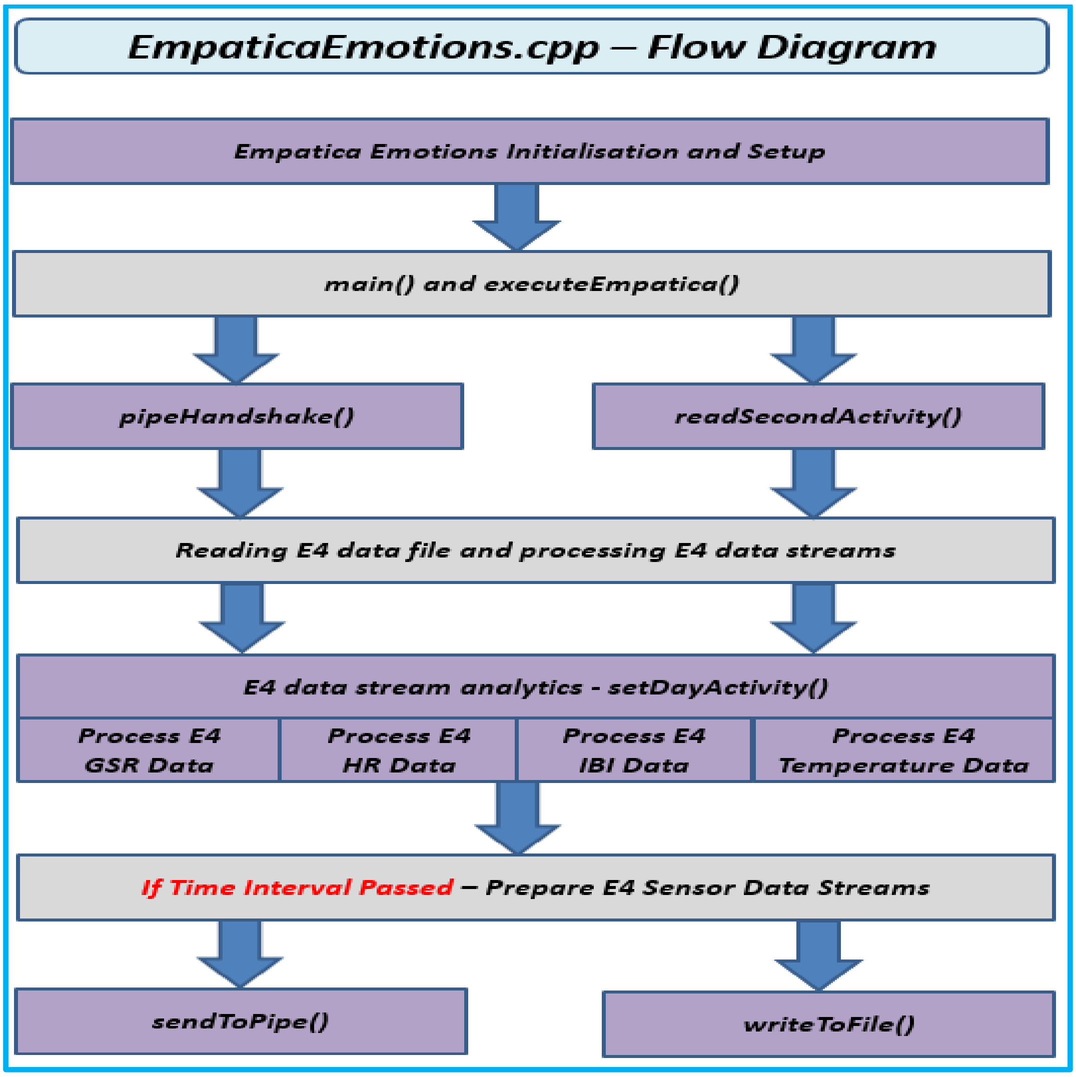



**Figure 4-13 EmpaticaEmotions - Flow Diagram**

The setDayActivity() method is responsible from processing the E4 data streams for GSR, HR, IBI and Temperature. The data streams from each physiological sensor on-board the E4 device are computed to produce individual mean per sensor values based on a pre-determined time tracking period. The raw E4 sensor data stream values used in the mean and time period related computations are also available if required for additional processing.

The EmpaticaEmotions adaptor prepares the E4 sensor data streams for transmission to the EFS via the sendToPipe() method. The E4 data streams are also written out to a separate data file/database for any additional related analytics.

**EmpaticaEmotions data manager:** The EmpaticaEmotions data manager represented in Figure 4-14 EmpaticaEmotions Data Manager - Flow Diagram also follows the data manager diagram template outlined in Figure 4-8 Sensor1...n Data Manager. The EmpaticaEmotions data manager is responsible for formatting and preparing the wearables sensor data streams received via the pipe server for final processing by the EFS as referenced in relation to the Filter code in the previous section. The flow diagram below is self-explanatory and provides the names of the methods used in the EmpaticaEmotions data manager.

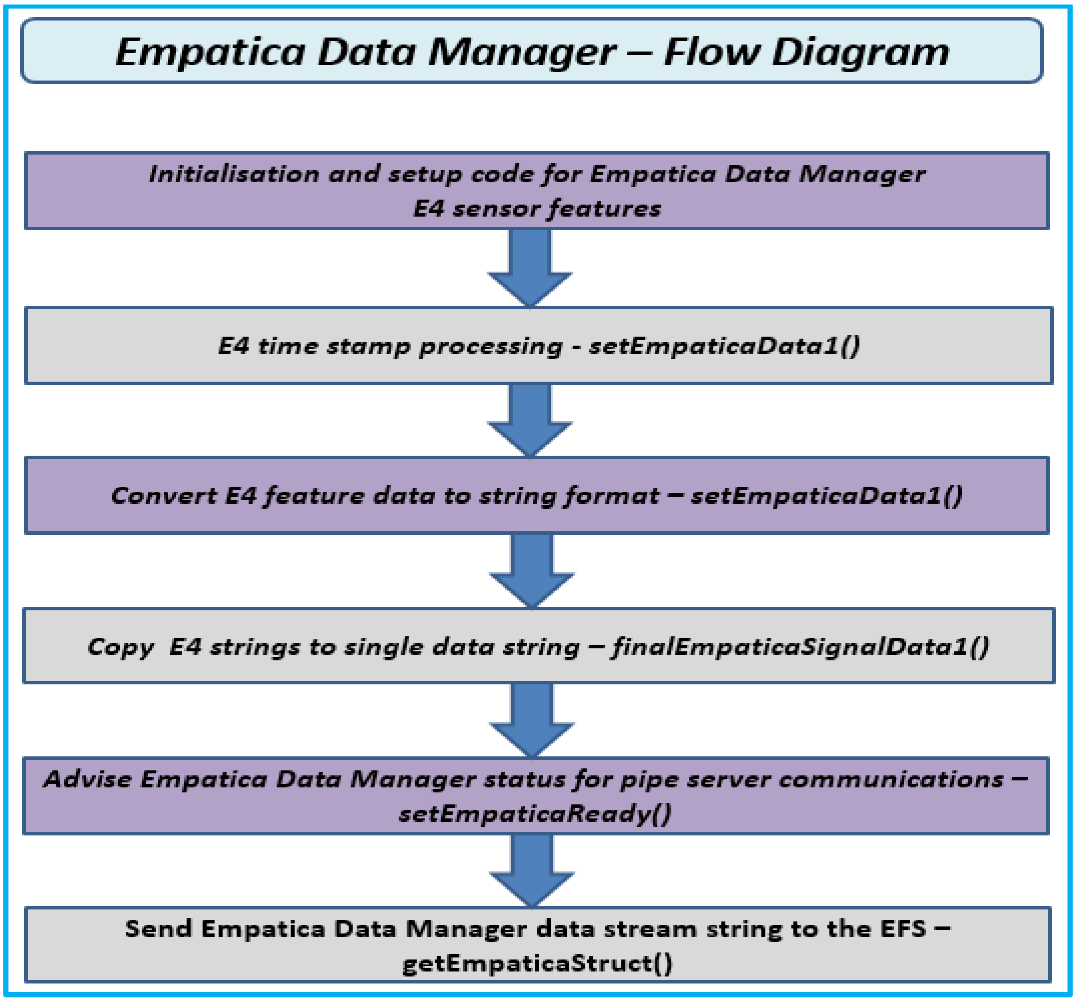



**Figure 4-14 EmpaticaEmotions Data Manager - Flow Diagram**

**Software artifacts extracts:** Selected software artifacts extracts relating to this section are provided in the appendices to this thesis in volume 2 of 2.

As part of the engineering and development cycle of the EFS platform, additional research was conducted into other sensor modalities. The next section of chapter four provides an overview of the additional research work carried out on other sensor adaptors and technologies for the EFS prototypical solution.

## 4.4 Affective Computing Other Sensors and Related Technologies

This section discusses additional sensor adaptors that were engineered and developed for the EFS as part of the research conducted. It also provides details on other related technologies that were investigated for potential sensor adaptor development and implementation purposes.

### 4.4.1 Prototypical Solution Other Sensor Adaptors

This section discusses two other sensor adaptors that have been engineered, developed, integrated, and tested for the EFS platform.

**EpocEmotions sensor adaptor:** The diagram below in Figure 4-15 EpocEmotions - Flow Diagram represents the EpocEmotions brain computer interface adaptor that was developed and integrated with the EFS. The Emotiv Epoc BCI has already been introduced in chapter two. At the early stages of the research, it was decided to investigate BCIs and their potential for AC research.

This led to a number of in-lab research trials and the development of the EpocEmotions adaptor for the EFS. The Epoc BCI headset used in these research trials had head mounted sensors that needed to be moistened with saline solution. This was quite an overload during testing phases so it was decided to also build in an option to use a software based simulator of typical emotion related brain signals provided for the Epoc by Emotiv. In the diagram below the exectuteEmoTiv() refers to the actual live BCI headset while the executeEmoComposer() refers to the software based simulator that could also be interfaced with the EFS.

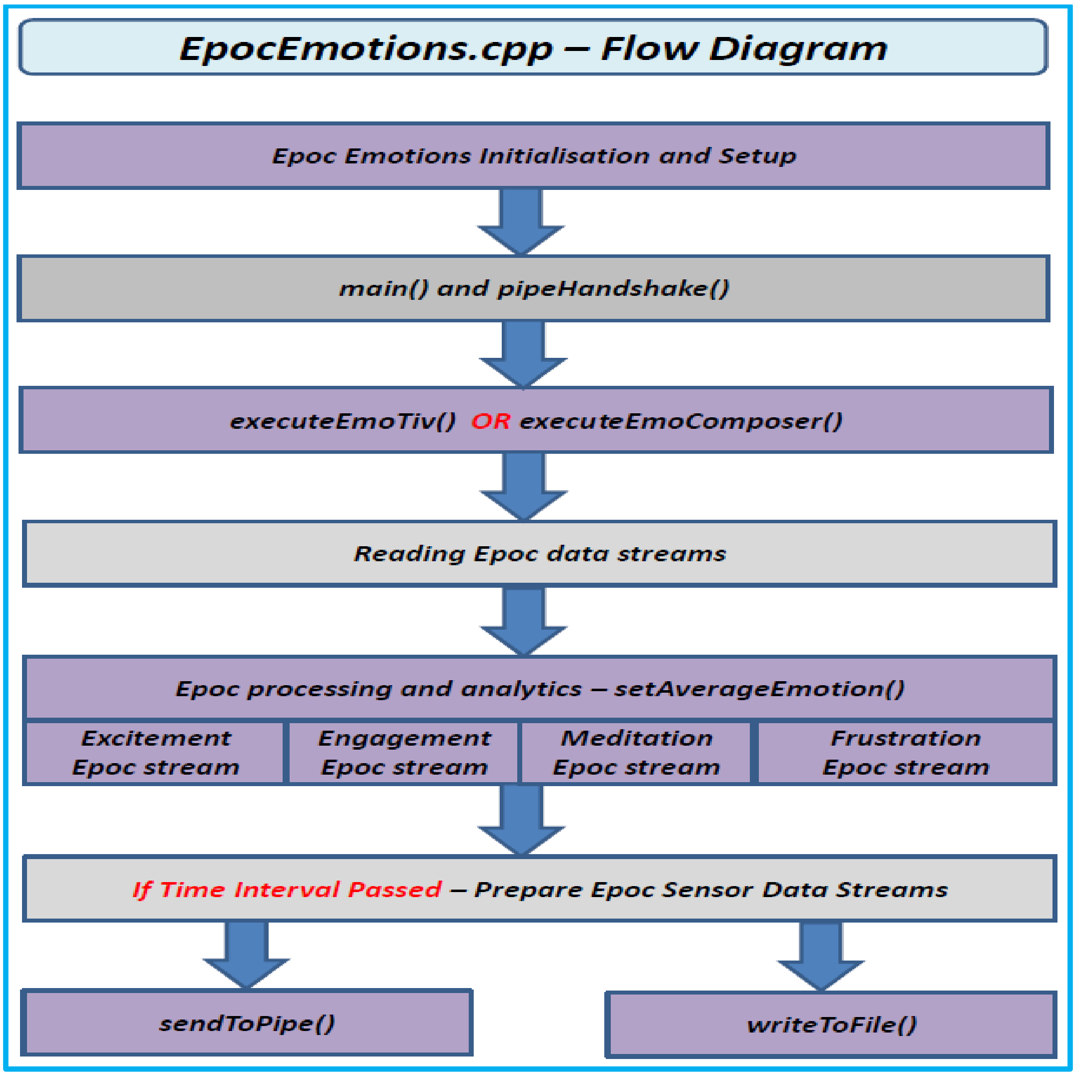



**Figure 4-15 EpocEmotions - Flow Diagram**

The EpocEmotions adaptor was designed to capture emotion related brain signals for Excitement, Engagement, Meditation and Frustration from the Emotiv Epoc BCI SDK. Once captured, these data streams very much followed the same processing analytics as the two previous adaptors. The EpocEmotions has also been engineered such that applied BCI and AC related algorithms can be developed and integrated into the adaptor in the future.

**EpocEmotions data manager:** The Figure 4-16 Epoc Data Manager - Flow Diagram represents the customised data manager that was developed for the EpocEmotions adaptor. The Epoc data manager follows the same logical processing flow as the other two adaptors already discussed.

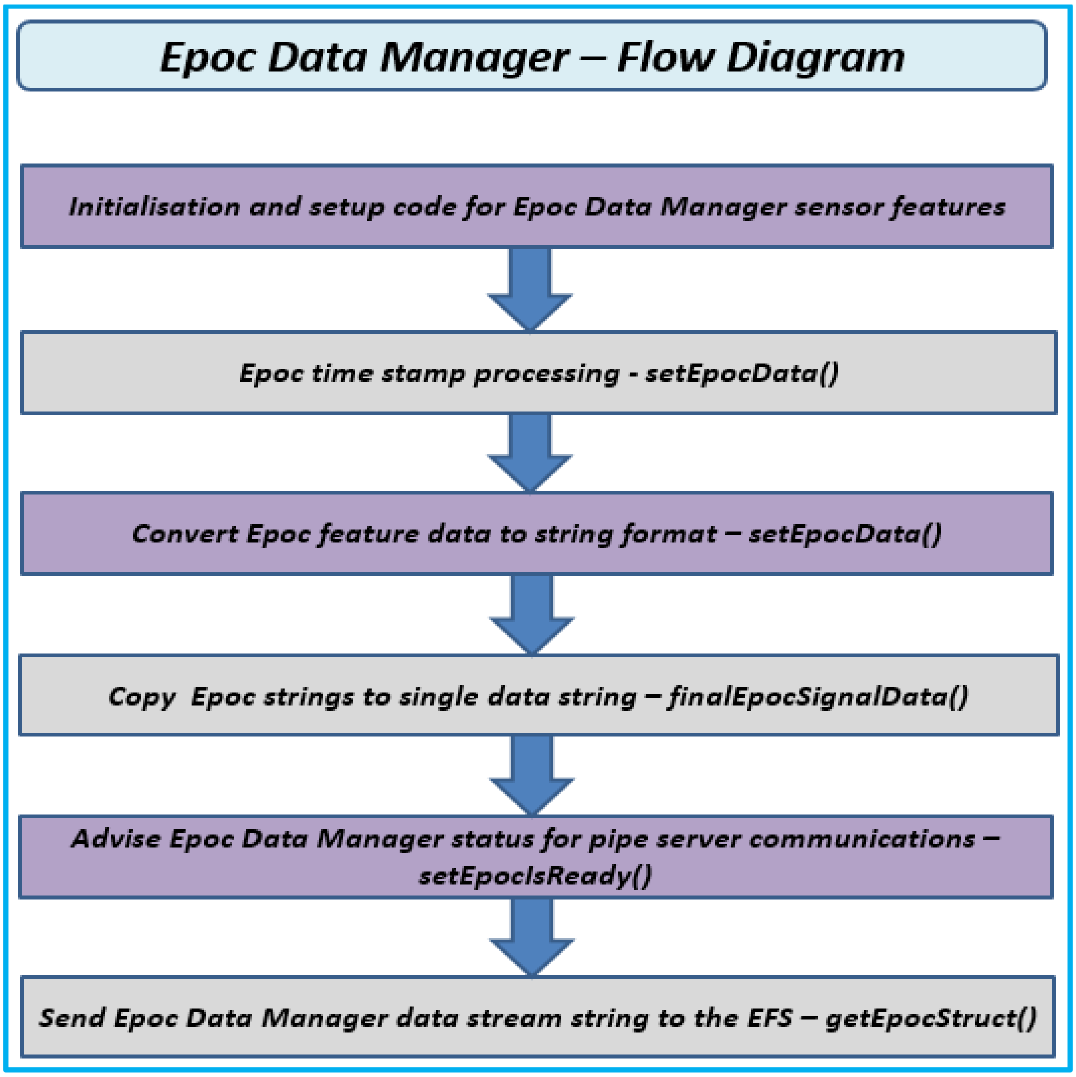



**Figure 4-16 Epoc Data Manager - Flow Diagram**

**Software artifacts extracts:** Selected software artifacts extracts relating to this section are provided in the appendices to this thesis in volume 2 of 2.

**Miner sensor adaptor:** Thesis research conducted into stress and quantified self and how computer inputs could be used to capture affective data, led to the investigation and development of the Miner sensor adaptor. The EFS Miner sensor adaptor is engineered to interface with the Workrave software which is a software program designed to assist in the recovery and prevention of Repetitive Strain Injury (RSI)[16]. Workrave is deigned to capture both mouse and keyboard PC inputs and to provide related reporting data. The Miner EFS sensor adaptor was developed to launch the Workrave program with the executeWorkrave() method in Figure 4-17 (Workrave) Miner - Flow Diagram below.

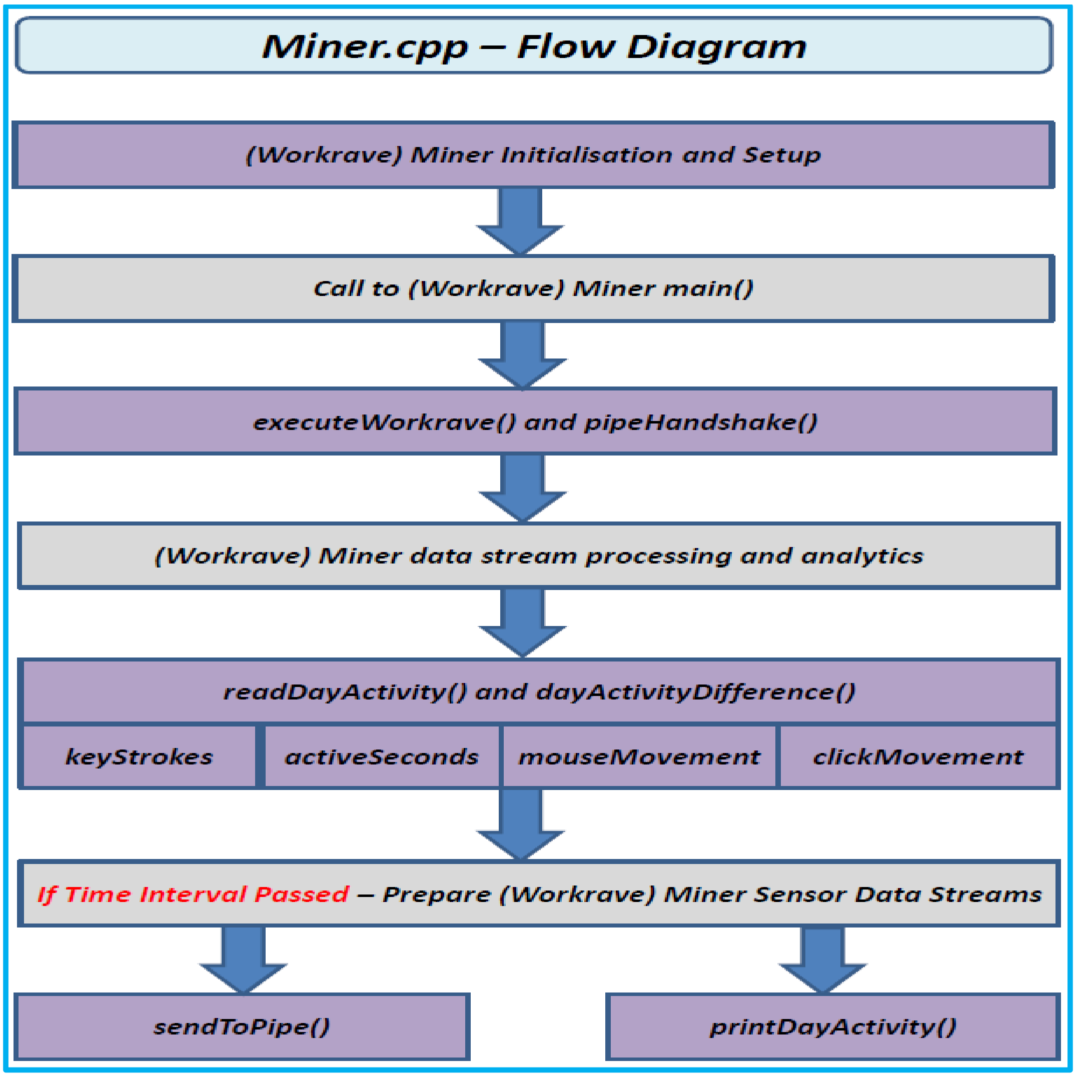



**Figure 4-17 (Workrave) Miner - Flow Diagram**

16 http://www.workrave.org/

The Miner adaptor developed for the EFS captured both keyboard and mouse input data that could be used for AC related user input analytics. The EFS was used in SIGMA based experiments which captured a fusion of EmotionViewer and Miner data during the early stages of the thesis research. The Miner remains an integrated adaptor with the EFS and has the potential to be developed further for detailed AC analytics relating to computing inputs. The Miner flow diagram above also represents similar functionality to that already discussed and is not expanded further in this section.

**Miner data manager:** The Figure 4-18 (Workrave) Miner Data Manager - Flow Diagram**Error! Reference source not found.** represents the customised data manager that was developed for the Miner adaptor. The Miner data manager follows the same logical processing flow as the other three adaptors already discussed.

The four adaptors examined this far have all been engineered, developed, integrated, and tested with the EFS. All adaptors are in varying stages of development and can be further engineered to incorporate various AC statistical and machine learning methods, algorithms, and techniques.

As pointed out to the reader, both the vision and wearables sensor adaptors are the main focus of this thesis research. The two sensor adaptors (EpocEmotions and Miner) introduced in this section provide validation of other sensor modalities for AC research and how the EFS architecture has been engineered and designed for multi-sensory fusion potentials.

**Software artifacts extracts:** Selected software artifacts extracts relating to this section are provided in the appendices to this thesis in volume 2 of 2.

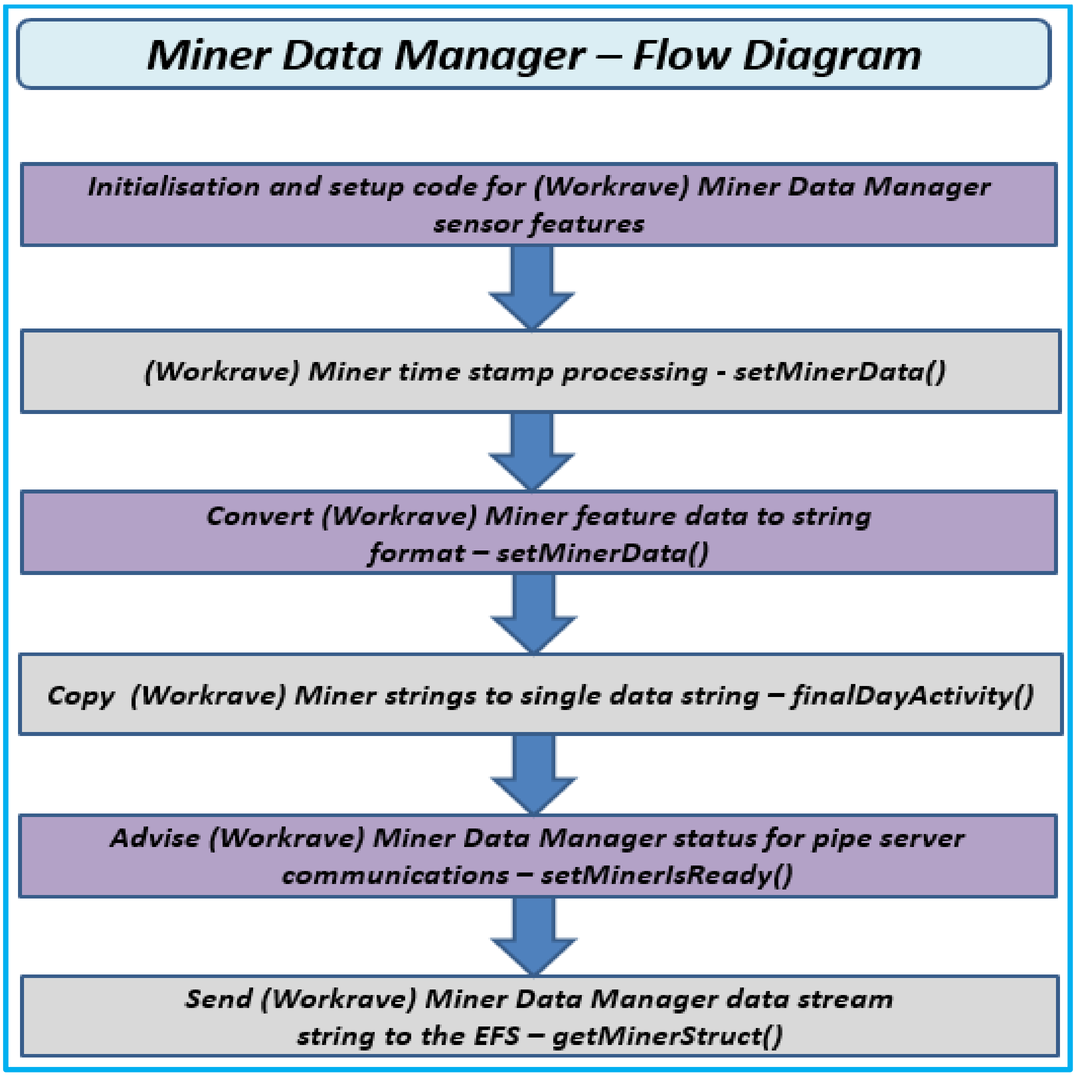



**Figure 4-18 (Workrave) Miner Data Manager - Flow Diagram**

### 4.4.2 Prototypical Solution Related Technologies

As well as the four adaptors already developed and integrated with the EFS, research was conducted into other related technologies as to their potential for integration with the EFS platform. A number of these technologies are briefly outlined below.

**Affectiva Affdex SDK:** Throughout the research, the Affectiva technology has been evaluated on a number of occasions. The Affdex platform has already been discussed in chapter two and typical data streams from its vision classification capabilities have also been reviewed in chapter three.

While it was decided not to develop an Affectiva Affdex adaptor for the EFS, specific research was conducted using the Affdex SDK. Research relationships were also developed with representation from Affectiva's engineering staff. Affectiva provided research access to their SDK and documentation and sample demonstrators were developed. The Affdex platform was capable of providing not only emotion classification but also age profiling, culture and gender from the vision data captured.

Outside of intellectual property issues in terms of the Affectiva classification algorithms the platform is reasonably open. The Affdex SDK certainly has potential to be integrated as a vision adaptor for the EFS using the sensor generic adaptor template structure provided in chapter three.

**Microsoft Band 2 SDK:** The Microsoft Band 2 was discussed in chapter two and it was separately investigated as to its potential for AC research and EFS adaptor development. The Microsoft SDK was used to create a number of demonstrators that accessed the Band 2 physiological sensors. Software demonstrators were developed and tested to access various sensors on-board the Band for GSR, temperature and computed heart rate estimates. Research was also conducted on the Band mobile apps and the Microsoft Health Cloud services. From experience, the Band 2 connectivity was not always seamless and device pairing attempts across Bluetooth and mobile devices caused intermittent errors that generally required a software re-install or re-boot of the device.

From the research conducted, the Band 2 offers interesting development potential for AC services, particularly in the eHealth domain. Microsoft's decision not to produce a Band 3 (Bowden, 2016) is certainly a factor to consider in any future development using this wearable device. That said, the research conducted was certainly beneficial to this research thesis. Provided that Microsoft continue to provide support for the SDK it is feasible that an adaptor similar to the EmpaticaEmotions could be engineered for the EFS using the Band 2 wearable device.

**Mobile Agitation Tracking (MAT) and the Real Sense SDK:** As discussed, the MAT system was also developed using the Real Sense SDK. Since the original version of MAT was developed the research has focused on raw facial landmark data extracted using a standard 2D camera integrated with the Real Sense SDK. SIGMA researchers are also working towards the development of a customised AC classifier using a support vector machine learning algorithm (Healy, Keary, & Walsh, 2017). MAT has the potential to be further developed and integrated into the EFS as a dedicated vision adaptor.

## 4.5 Software Architecture and Development Considerations

This section conceptually relates back to Dasarathy's fusion architecture and in particular discusses the AC-Strata and S-Strata and how the EFS prototypical solution references and integrates the concepts from both models. It also presents a commentary on prospective developments in relation to the EFS prototypical solution.

### 4.5.1 Prototypical Solution Software Architecture Review

The main focus of chapter four was to take the abstract stratification and conceptual discussions of chapter three and to present then in the structure of a prototypical solution that was engineered and developed in the form of the compiled EFS software artifacts.

The first section of chapter four presented a non-technical overview of the EFS which demonstrated the multi-sensor and fusion capabilities of the platform. This was followed by a number of high-level representations that described the EFS processing framework, sensor processing and a sensor generic adaptor template to be used for the development of current and future sensor adaptors to be integrated with the EFS.

The software core of the EFS was also presented in the first section. This used a context diagram to introduce the main fusion modules of the EFS. The EmotionDataFusion and the Filter code base were both presented using flow diagrams. This section also provided a generic outline for a sensor data manager and briefly explained its functionality in terms of data stream processing in the EFS.

The next two section specifically addressed both vision and wearables adaptors developed for the EFS. The section on vision presented a general overview of the adaptor and a discussion on the underlying Real Sense technology used in its development. The EmotionViewer and its related data manager flow diagrams were used to explain the adaptor algorithm processing functionality. The EmpaticaEmotions wearables adaptor was also presented with a general overview of core Empatica software components used in the adaptor development. The discussion on the code base presented flow diagrams for both the EmpaticaEmotions adaptor and its data manger.

The fourth chapter section discussed additional technical research that was conducted into other AC sensor modalities. Both the EpocEmotions and the Workrave Miner adaptors were briefly introduced and explained. This section provided examples of how the EFS could handle additional sensor modalities with

AC potentials and how they were also built and deployed based on the sensor generic adaptor template introduced in section one of the chapter. This also highlighted the multi-sensory and fusion capabilities of the EFS. Section four also introduced other adaptors that have been researched in relation to the EFS (Affdex, Microsoft Band 2 and MAT) and their potential for integration into the EFS platform.

The EFS is an evolving prototypical AC sensory fusion platform and the below discussions highlight some general commentary in relation to the current version of the software artifacts.

**Stratification models:** Currently the EFS platform incorporates various elements of the S-Strata at an individual sensor level and the AC-Strata at the multi-sensory fusion level. The S-Strata provides for ever increasing levels of AC related intelligence to be specifically developed and customised for a sensor adaptor. For example, the current EmotionViewer possesses AC reasoning capabilities while the EmpaticaEmotions adaptor currently lacks embedded AC reasoning capabilities. The EFS platform is designed such that ever increasing AC intelligence/functionality (as outlined in the stratification models of chapter three) may be implemented at both the individual adaptor sensor level (S-Strata) and at the higher sensory fusion domain related level (AC-Strata).

**Temporal reasoning:** The EFS sensor adaptors are designed to capture and process timestamp data for all AC related feature data. The EFS can be configured such that all sensors report as an ensemble for a pre-determined time period. Timestamp data is critically important and is captured to enable drill down into more fine grained fractional changes in the sensor feature data streams. Temporal reasoning is a critical aspect of AC research and sensory adaptors developed for the EFS may be engineered with highly sensitive and customised temporal reasoning capabilities as required in the future.

**AC sensory decision fusion:** The current iteration of the EFS has no specific fusion scheme implemented in its current code base. Presently the EmotionViewer adaptor makes its own affective state classification decisions. The EmpaticaEmotions adaptor currently captures raw sensor data streams but has no applied affective decision making capabilities. The EmpaticaEmotions adaptor is designed such that it can be updated with AC decision making capabilities once established algorithms are developed/available/tested for physiological sensory data. This is also the case for the other adaptors discussed (EpocEmotions and Miner).

In certain circumstances, customised EFS sensor adaptors may need to interface with proprietary cloud based AC semantic and ontological reasoning services, and factors such as connectivity, speed, security, intellectual property, and third party services will be important considerations in such future adaptor engineering developments.

### 4.5.2 Prototypical Solution Prospective Developments

The following presents discussions on the prospective development potential of the EFS platform and its related software artifacts.

**AC sensory fusion schemes:** From a fusion perspective, the architectural design of the EFS allows for the implementation of decision level (S-Strata focused) or feature level (AC-Strata focused) fusion schemes or even a hybrid scheme across the EFS platform. The most likely future scenario is a range of sensor adaptors with a combination of in-built AC reasoning capabilities, partial reasoning or customised AC classifiers that may need to be developed.

With reference to the S-Strata, the implementation of decision level fusion involves each adaptor integrated with the EFS having its own AC decision making capabilities. If this is the case, then each adaptor reports an affective state which is then processed at a higher level (AC-Strata) to arrive at the most probabilistic affective outcome for a particular instance in time. The EFS platform can be easily engineered to implement such a decision fusion scheme. This will involve each adaptor having access to its own emotion classifier based on the relevant sensor modality. With all sensor adaptors reporting their own affective decisions, the fusion part of the EFS (AC-Strata) needs to apply AC related decision making and statistical voting algorithms to arrive at the best probabilistic decision from each of the affective states reported by the sensor modalities.

Feature level fusion may also be implemented in the EFS provided that the raw feature data is accessible. All EFS adaptors are designed to report all available sensor features as individual vectors. These individual feature vectors can then be fused into a sensor ensemble feature vector for higher level feature fusion based processing. The complexities of feature level fusion have already been debated and in the higher layers of the EFS (AC-Strata), advanced AC statistical and machine learning classification algorithms need to be applied to the ensemble vector. This feature level scheme will require highly specialised development but it has the potential to address far more of the cross feature analytics (SS-C-FD), contextual analysis (SS-C), and quality control (SS-QC) aspects discussed in relation to the AC-Strata stratification model. This feature level fusion scheme also offers potential for the computation of additional features (SS-C-FD) to be created from the original feature vectors of the various independent sensors.

The EFS can also be engineered to provide for a combination of both fusion schemes in a hybrid fusion scheme approach. This is already the tendency for the current version of the EFS where there is a combination of adaptors delivering raw features and others providing affective state decisions (EmotionViewer). Whatever approach is taken, the current prototypical EFS solution offers the potential for further developments and application of an appropriate fusion scheme.

**AC semantic, ontological and personalised reasoning:** One of the main work packages in the SenseCare project is investigating and researching how semantic and ontological reasoning technologies are used in AC. The research conducted as part of the SenseCare project has identified a number of relevant sensor and emotion ontological resources such as the Sensor Model Language (SensorML) (Open GeoSpatial Consortium, 2018); W3C Semantic Sensor Network Integration Group (SSN) (Open GeoSpatial Consortium, 2018); EmotionOnTo (Gil, Virgili-Gomá, García, & Mason, 2015) and the EmotionOntology (Hastings, Ceusters, Smith, & Mulligan, 2011).

Any detailed discussion on these semantic and ontological technologies is outside the scope of this thesis but they have been included here to highlight the specific aspects of the AC-Strata where both sensor and emotional semantic reasoning infrastructure may be used to add higher level and domain specific (eHealth) affective reasoning capabilities to an AC platform. It is also evidence of the work underway and a realisation that affective decision making is not just exclusively about the identification of a solo emotional state in an individual, rather it is a compendium of many complexities such as context, domain knowledge, environment, personalised, physiological and many other forms of real-world data.

Semantic and ontological engineering also relates to the many discussions had around personalisation and the development of customised AC classifiers with subject specific knowledge at its core. Such personalised AC platform services need to be highly secured due to their personal profiling capacities and also need to be supported by comprehensive backend personal data management platform services. This highly controversial aspect of AC data security and sensitivity is discussed next.

**AC reproducibility potentials:** As part of this research an IEEE paper titled, The role of reproducibility in Affective Computing was presented at the 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (Engel, Keary, Berwind, Bornschlegl, & Hemmje, 2017). A number of key points from this paper in relation to AC, reproducibility futures, security and data sensitivity are reproduced below.

The paper presented a general definition by De Roure who defines reproducibility as *reusing a research object with a change to some circumstances, inputs, resources or components in order to see if the same results are achieved independent of those changes* (De Roure, 2014), (Engel, Keary, Berwind, Bornschlegl, & Hemmje, 2017), [p. 2009].

In AC platforms in the future, the process of capturing, fusing and analysing a user's cognitive/affective state will take place across a range of work, social, home, and personal care environments and can last for highly extended time durations. During any AC monitoring period, personal data will be generated such as sensory data, clinical data, care plan/execution data, and communications. In fact, all of this data must be managed securely, sensitively, and in compliance within existing regulatory frameworks and laws.

From May 2018 onwards, new personal (sensitive) data policies, in the frame of the General Data Protection Regulation (GDPR) (EU, 2018) will be enforced to transparently regulate personal data management, processing and transmission. Essentially the GDPR *replaces the Data Protection Directive 95/46/EC and was designed to harmonize data privacy laws across Europe, to protect and empower all EU citizens data privacy and to reshape the way organizations across the region approach data privacy* (EU, 2018), (Engel, Keary, Berwind, Bornschlegl, & Hemmje, 2017), [p. 2011].

Part of the new GDPR regulation will be a novel policy about the right of explanation, (Goodman & Flaxman, 2018) which will protect data subjects in relation to decisions made about them by automated data/cognitive processing systems. The GDPR regulations state that the *data subject should have the right not to be subject to a decision, which may include a measure, evaluating personal aspects relating to him or her which is based solely on automated processing and which produces legal effects concerning him or her or similarly significantly affects him or her. Such processing includes profiling that consists of any form of automated processing of personal data evaluating the personal aspects relating to a natural person, in particular to analyse or predict aspects concerning the data subject's, health, or behaviour, where it produces legal effects concerning him or her or similarly significantly affects him or her* (EU, 2018), (Engel, Keary, Berwind, Bornschlegl, & Hemmje, 2017), [p. 2011].

The GDPR extract above could well be interpreted as directly relating to the reproducibility of affective decision making by AC platforms/services. The research paper specifically addresses the current black box nature of a range of AC based sensory devices and presents a study in relation to a typical AC vision adaptor where the underlying algorithms used in the affective decision making may not necessarily be exposed from a reproducibility perspective. The authors argue that in the future, AC black box approaches may not comply with the new GDP policies and directives. Reproducibility and developments in relation to the GDPR are key considerations and thus must act as a fundamental driver in all future developments of AC platforms and their sensory adaptor interfaces.

That concludes a section which reviewed the EFS prototypical solution software architecture with reference to the stratification models, temporal reasoning and decision/feature/hybrid fusion. It also provided a glance into the prospective development potentials and opportunities for the EFS software architecture. This included applied discussions on complex fusion schemes, semantic, ontological, and personalised reasoning, and the GDPR which acts as a vital regulatory driver for any future AC research, engineering, and development.

## 4.6 Summary

Chapter four has taken what is primarily a series of conceptual and theoretical proposals and guidance, and has produced an actual prototypical AC related series of software artifacts known as the EFS. The technical aspects of the EFS and its related sensor adaptors have been presented and explained throughout chapter four. Indeed various iterations of the EFS has been used for a number of AC related trials at the SIGMA facility over the past number of years. The EFS engineering and development work conducted has also been an influential factor towards the formulation and winning of the EU RISE SenseCare project that is being led by CIT (SenseCare Consortium, 2016).

Eventually through software engineering efforts over the years of this thesis research, the EFS platform reached a level of maturity whereby it could be used as infrastructure for extensive AC experimentation. A version of the EFS platform exclusively integrated with vision and wearable sensor adaptors was produced and was used in a battery of novel AC experiments across a total of thirty three signed up participants.

Chapter five now presents the next stage of the research conducted using the software artifacts that have been combined to form the EFS prototypical sensory fusion platform. Chapter five provides full detailed background and explanations of the AC experiments conducted along with thesis hypothesis related data analytics and applied statistical reporting and analysis across the various evaluation phases of the research.

# 5 Evaluation

Chapter five is broken up into seven sections. The first section revisits the research hypothesis and provides a general overview of the experiments conducted. Section two discusses the theoretical and practical aspects of the design and organisation of the experiments while section three provides details and examples of the typical datasets that were produced from the AC experiment processes.

Section four to six address the statistical reporting and analysis of the experiments results. Section four presents reporting and analysis at a macro level across the experiments as a whole and provides analysis from vision, wearables and self-reporting perspectives. Section five provides statistical reporting and analysis at a micro level, providing an individual participant perspective. Section six provides details of further applied statistical techniques and investigations that were carried out on the datasets. Section seven provides an overall summary of the main findings and conclusions of the reporting and analysis work that was conducted.

## 5.1 Experiments Introduction

This section discusses the overall hypothesis evaluation process and also provides a general overview of the experiments that were carried out during the research evaluation phases.

**Hypothesis evaluation overview:** First and foremost, in order to formally investigate the thesis hypothesis, a number of the research objectives outlined in chapter one had to be achieved. These main objectives have been extensively documented in the previous three chapters. Chapter two provided the foundational research into the current state of the art in AC. This work led to the conceptualisation and formalisation of an AC platform architecture which was explained in chapter three. Following this, chapter four presented the EFS which was formally engineered into a prototypical solution implementation for use in the experimentation and evaluation processes.

These three chapters also respectively address the following stages of the hybrid methodology. The observation and problem analysis, and state of the art research stages were covered in chapter two, problem modelling and system design stages in chapter three, and the implementation stage in chapter four.

Experimentation is the next stage in the hybrid methodology and it is presented and explained throughout this chapter. The various sections also directly address thesis objectives TO7 on experimentation, TO8 on statistical processing, and TO9 on results, findings and conclusions.

Before advancing into the main detailed section of this chapter, for review and clarification purposes the thesis hypothesis from chapter one is repeated below.

**Thesis Research Hypothesis**

- ***$H^0$* -** *The fusion of affective sensory data from vision analytical systems with multi-sensory physiological analytical systems does not significantly increase the sensitivity and specificity (predictive performance) of emotion recognition when tested on subjects in typical emotionally generated situations or events.*

The remainder of this chapter will now present and explain the various phases of the experimentation and evaluation processes that were conducted in order to investigate the above thesis hypothesis. In particular, the more formal sensitivity and specificity investigations surrounding vision and physiological AC systems will be presented in the results, findings and conclusions sections of the chapter.

**Experiments general overview:** Each participant completed a total of nineteen experiments which were separated into five logical AC related groups. Each group of experiments were along a specific use case related theme and involved participants carrying out activities that were designed to create emotional responses.

Participants were provided with a brief explanation of each group of experiments before each battery of experiments were conducted. For example, one group of experiments involved manual dexterity with various objects designed to increase levels of irritation, frustration and possibly anger. Another group of experiments involved the completion of computer based interactive tasks expected to generate emotional responses. The emotional response data generated by participants were recorded from the facial expressions and physiological data using the vision and wearable adaptors engineered, developed, and integrated with the EFS.

After each experiment activity, the participant was asked to complete a self-evaluation form using the GEW. This part of the experiment aimed to capture a range of emotions that the participant personally felt while carrying out the experiment activity. All experiment related data captured was anonymised for all participants as per ethical standards established for the research.

On average, participant total involvement was for approximately one and a half hours. This time included all documentation (overview, consent forms, etc.), formally conducting the experiments, general discussions, devices set-up and calibration, experiment environment checks, self-reporting, and experiment sign-off procedures.

The following presents a brief overview of each group of experiments that were conducted.

**Experiments group 01 dexterity based object interactions:** This group of experiments required the participant to carry out four manual dexterity experiments with various objects designed to identify emotionally generated levels of irritation, frustration and possibly anger. The participant manipulated two puzzle objects, the opening of a slippery object and the set-up and activation of a mouse trap.

**Experiments group 02 cognitive based:** This group involved three cognitive recall experiments where a participant was asked to recall emotional related events (Happy, Sad, Angry, Fear…) that they have experienced or may experience in the future. The participant had to cognitively generate negative and positive emotions during this group of experiments. It was agreed that this was to be conducted silently. The first recall experiment related to negative emotions, the second was positive emotional recall and the third experiment gave the participant the option of either positive or negative recall.

**Experiments group 03 visual based:** This group of experiments involved a series of interactions with a selection of imagery expected to generate an emotional response in a participant. The first experiment used a short video sequence and the remaining four experiments used a selection of still imagery, each relating to a defined set of emotions.

**Experiments group 04 olfactory based:** This group involved a set of five experiments that used various smells that were expected to generate an emotional response in a participant. Each of the olfactory experiments were contained in a sealed jar and were presented in a pre-defined order without the use of a blindfold.

**Experiments group 06 gaming based:** This group of experiments involved the completion of two computer based interactive experiments expected to generate an emotional response in a participant. In the first experiment the participant played an interactive computer game based on the Stroop test (MacLeod, 2015). Once the first game in this experiment was completed, the participant was asked to try to beat their score in a second attempt of the same game under self-induced time pressure. The second experiment involved a reflex speed test that the participant played for approximately two minutes. The aim was for the participant to try and beat a reaction time of 0.2 of a second.

A full set of formal documentation with comprehensive experiment explanations has been developed for the AC experiments and is available in the appendices to this thesis in volume 2 of 2. The next section presents discussion on the design and organisation in relation to the AC experiments.

## 5.2 Experiments Design and Organisation

This section provides a discussion on the theoretical background and methodology used in the design of the experiments. It also highlights the ethical approval process carried out, presents an insight into the organisation of the experiments and provides a typical walkthrough of the protocol used in formally conducting the AC experiments.

**Experiments design methodology:** This section provides some theoretical background relating to the aims of research from an experimental design perspective with reference to the specific experiments conducted. It discusses the repeated measures design methodology that was used and explains how it was applied to the AC experiments.

In relation to experimental design, Field and Hole (Field & Hole, 2011) identify three principal aims of research which they discuss in their book under Reliability, Validity and Generality (Importance).

**Reliability:** One of the main aims under reliability is to ensure that the dependent variable(s) is measured as precisely as possible and that there is an unambiguous and objective definition of whatever it is that is being measured. Throughout the experimental research and in the use of the EFS prototypical solution, every care and attention has been applied in the capturing of reliable feature data measurements from those that participated in the experiments. This attention to reliability has also been rigorously applied during the follow on data analytics phases.

This has involved set-up and testing before experiments were conducted, having a consistent environment throughout all experiments, documenting the notification of any errors (hardware or software) where there may be possible impacts on the data, agreed equipment calibration time periods and full quality assurance of the automatic data captured and in the compilation and production of the related datasets produced.

**Validity:** Experimental validity is critical and Field and Hole (2011) divide it into both internal and external threats which are discussed below with relevance to the AC experiments.

**Threats to internal validity:**

- **Group threats:** Field and Hole (2011) stress the requirement for randomisation as a way to addressing this threat. Generally speaking the participant selection for the AC evaluation experiments was quite random by nature but it was primarily within an academic community setting.
- **Regression to the mean:** This is explained by Field and Hole (2011) with an example to do with increased road accidents in the year 2001 (Field & Hole, 2011), [p. 58]. If after an intervention, road accidents reduced in subsequent years, the police intervention policy may be deemed an outstanding success. Field and Hole (2011) argue that this may not be a valid conclusion and indeed may be just the regression to the mean due to a large number of accidents in the first instance. This validity factor could also be considered in relation to the complexities of human emotion in the context of the previous discussions on stimulus-response and individual-response (Andreassi, 2007). Any sudden change in a subject's mood may in actual fact be a regression to their own personal affective mean rather than some unexpected emotional state change.
- **Time threats:** This factor relates to how time can change the experimental process as it will impact on the participant, environment and many other variables even down to the equipment involved. Time was not a major issue in the research conducted as each participant was scheduled to complete all experiments in one sitting. Very early into conducting the experiments for the first few participants it was learnt that a short break had to be given after the third group of experiments. This was required as there was quite a heavy task and cognitive load involved

in the various groups of experiments, and especially with the mandatory self-reporting after each individual experiment was conducted.

- **History:** This largely relates to events in the life of the participant that may have a bearing on the experiments validity. Again this is extremely relevant to emotional related research and was a factor for the experiments conducted. This was most significant during the cognitive recall experiments where some participants found it difficult to get negative emotional thoughts out of their mind and had problems switching between negative/positive emotional states.
- **Maturation:** As the subject matures there may be an impact that needs to be considered, particularly if it is a long-term experiment and the maturity of the person is not a key factor. Maturation is a very interesting field for AC and as the research experiments are of keen interest to the SenseCare project it will be a relevant factor in future research. For the experiments conducted, maturation/age of the participant was not taken into account as a data feature in the related analytical processes but this could certainly be applied in future AC research work.
- **Instrument change:** This covers the calibration of equipment and could also apply to a researcher getting better or worse at conducting the experiment(s). Both of these factors are relevant to the experiments carried out. In relation to equipment, the E4 wearable had to be given time to calibrate with the person's physiological body signals. To address this, all participants had an introductory period of at least twenty minutes, which efficiently provided the required calibration time before the various groups of experiments started. In relation to the researcher involved, an

experimental protocol (discussed below) was used to ensure that there was a coherent format and flow to all five groups of experiments.

- **Differential mortality:** This addresses the case where participants may opt out of the research programme for some reason. By its very nature, emotional research can be impacted by this issue and it needs to be managed very carefully. The research conducted was within extremely strict ethical guidelines and differential mortality was not a factor for the experiments conducted.
- **Reactivity and experiments effects:** Field and Hole (2011) explain that *people's reaction to having their behaviour measured may cause them to change their behaviour* (Field & Hole, 2011), [p. 60]. In the literature, this is generally referred to as the Hawthorne effect which *concerns research participation, the consequent awareness of being studied, and possible impact on behavior* (McCambridge, Witton, & Elbourne, 2014), [p. 267]. This factor generally sums up to the reality that the experiment may change the participant and the experiment may influence the participant during the actual experiment itself. In conducting the AC experiments, the involvement of the researcher was mandatory to ensure flow, consistent application and in dealing with the hardware and software involved. Also considering the fact that the participant knows that the experiments involve emotional responses and that there are expected outcomes, there was an increased awareness of the Hawthorne effect and its possible impact while conducting the AC experiments.

**Threats to external validity:**

- **Over-use of special participant groups:** This relates to the importance of varying the types of groups that participants are picked from rather than the same type of grouping. Field and Hole (2011) discuss this factor in relation to volunteers vs non-volunteers. The AC research experiments conducted were primarily designed as being laboratory based and have been generally associated with a research student cohort.
- **Restricted numbers of participants:** This relates to statistical power and the generalisation of experimental findings to the population as a whole (Field & Hole, 2011).

**Generality (Importance):** In relation to the third aim of research, Field and Hole (2011) point out the importance of how experiment findings *will generalise to other groups of participants in other times and places* (Field & Hole, 2011), [p. 63]. This has such relevance to the affective sciences and has been a major influence on the success of FACS based research (Ekman & Friesen, 1978). Field and Hole believe that the best measure of generality is by empirical testing.

Empirical testing involves the *replications of the experiments by other people in other circumstances* (Field & Hole, 2011), [p. 63]. The replication of experiments is highly topical at the moment and has already been discussed in chapter four with reference to scientific reproducibility. Reproducibility has been addressed as part of this thesis research and particularly in relation to the AC experiment processes. Considerable work has been conducted in relation to the design and delivery of the various experiments to ensure that they may be repeated under varying circumstances and participants in the future.

**Repeated measures experiment design methodology:** The repeated measures experiment design methodology uses the same participants in a number of experiment conditions. The participant produces one result for every condition in the experiment. This thesis research principally used the repeated measures methodology with slight variations for the measurement of affective states. These variations related to the fact that all nineteen experiments were set out in thematic experiment groups and also that the participant could produce more than just one result during the sensor data analytics and also in their personal self-reporting of each experiment.

Field and Hole (2011) discuss economic factors as one of the main drivers for repeated measures design. Using the same subject multiple times can be extremely beneficial in terms of time and effort. This was indeed a factor for the AC experiments conducted, considering the set-up time, equipment calibration efforts, availability of participants, and the need for focused attention in order to get into the correct mind-set for experiment participation.

Sensitivity is a key part of this research and it is a major consideration in the distinguishing of *all the random noise produced in [our] data by the fact that participants differ from each other* (Field & Hole, 2011), [p. 79]. The repeated measures methodology can lessen random noise by reducing any problems and time factors involved in the participant matching process. Using the same participant in all conditions increases experiment sensitivity and thus has fewer sources of random personal variation.

On a less positive note, Field and Hole (2011) discuss the carry over effects from one condition to another. They explain that this relates to where participant performance may vary from experiment to experiment and from condition to condition. Some of the means to address the carry over effects include avoiding participant fatigue, randomisation of subjects, randomisation of experiment conditions, watching for increased practice in the tasks and looking for effect in the order of presentation of experiments or conditions.

The thesis experiments conducted aimed to address a number of these issues and specifically incorporated subject randomisation, experiment randomisation, minimisation of over practice opportunities for participants, and periods of rest to avoid participant fatigue.

One other aspect raised by Field and Hole (2011) is the need for conditions to be reversible. By this they mean that having a participant in one condition does not have irreversible effects that prevent the subject being used in another condition. For example an experiment that puts a participant into an extreme situation such that they are unable to participate in the next repeated measures experiment.

From the experience of conducting the thesis experiments, this aspect was encountered in a minor way. Participants certainly found cognitive strain with emotional switching in their brain and also with the self-reporting tasks. This aspect came out strongest with the cognitive recall based group of experiments and specifically applied for some participants who had difficulty in emotional switching and in getting negative thoughts out of their head.

**Ethical approval process:** Prior to conducting the experiments for this thesis a formal ethical approval process was carried out. This involved the completion of required documentation and a formal submission to the CIT Ethics Approval Committee.

As part of the submission, a concise statement in relation to ethical issues raised by the research and how they were to be managed was requested. The following extracts below from the ethics approval documentation highlights the ethical management issues that were addressed in relation to the experiments.

**Ethical issues arising:** All experiments were designed with ethical considerations in mind. Thus no ethical issues were expected once each participant had read and understood the experiments and what was expected of them.

**Personal data:** No personal data was recorded or used for purposes other than affective computing related research. Participants were not recorded in any video format, only their video frame data alone was processed by the EFS.

**Right to cease participation:** The participant had the right to decide if they did not wish to participate at all or to participate only in selected experiments.

**Emotional disturbance:** Where an experiment might involve any disturbing emotional thoughts/images, the participant was always given the option to decide to abandon the experiment if they wished.

**Abandonment of an experiment/task:** The researcher could also decide to abandon the experiment at any stage, if it was decided as the most appropriate course of action at the time.

As part of the ethical approval process, the organisation of the experiments and a formal participant protocol was also presented for review. The following documentation was presented for approval for conducting the AC experiments.

**Participant informed consent form:** This form was adapted for the experiments and was based on a standard form from the CIT Ethics Approval Committee.

**Experiments protocol:** All experiments have followed a standard protocol in terms of participant communication, explanations prior to the experiments, set-up, running the experiments and final wrap-up. This protocol is discussed further in the next section.

**Experiment groups:** Each group of experiments were treated as a separate thematic entity as part of the repeated measures design. This involved each group having its own unique set of documentation and a tailored experiment protocol. For each group of experiments the participant had to read the overview page, acknowledge their understanding by their signature and they were also given time to ask any questions prior to starting the set of experiments in the group. Further details in relation to the individual experiment protocols are available in the experiments documentation contained in the appendices to this thesis, volume 2 of 2.

**GEW self-reporting:** The GEW form was slightly modified for the experiments to incorporate the recording of the start and stop time for each experiment task. A description was also provided to the participant on how to use the GEW for self-reporting after each experiment was completed.

**Data protection:** Details on the procedures in relation to access, retention, and destruction of the datasets created and processed also had to be provided to the ethics committee. The handling and storage of sensitive data is of critical importance in research governance and has been taken very seriously for this research. Each participant in the research has been informed of the extent of information that is gathered on them and that it is exclusively stored anonymously. All data that was gathered was necessary for the study and no additional unnecessary data was collected.

The data collected from each participant was formally defined as both written documentation and electronic information. The data includes records of consent, characteristics of the participant group, observations made by the researchers during experiment completion, participant feedback and self-reporting of emotional experiences and data collected by the EFS sensors.

All participants' written documentation is stored securely and under the control and authority of CIT. All electronic data is stored anonymously by use of defined identifier codes to protect anonymity of the experiment participants. All data collected, both paper and electronic forms will be stored at CIT for as long as this specific AC research is being conducted. Upon completion of the research, all data will be deleted within a three month period. Research related handwritten data will then be destroyed as confidential waste, and electronic data directly relating to the participants sensory data will also be deleted. SIGMA researchers at CIT reserve the right to produce additional datasets (based on the AC experiments original datasets produced) for future related research purposes.

After a number of minor adjustments based on feedback from the CIT Ethics Approval Committee, the submission was successfully accepted and the formal process of participant recruitment was started for the experiments. The full set of ethics approval documentation is contained in the appendices volume 2 of 2 of this thesis.

**Experiments organisation and participant recruitment:** Following the ethical approval process the recruitment of participants started. A number of cohorts were targeted during the recruitment campaign using targeted emails, guest lectures, posters and flyers.

The following summarises the background of the main cohorts the participants came from:

- **International Space University (ISU):** These were students taking a space studies research programme at CIT organised by the ISU[17].
- **CIT researchers:** Researchers across a number of research departments in CIT.
- **CIT students:** General recruitment from the CIT student base.

Before discussing the experiments protocol, a top-level review of the experiments structure is appropriate. As discussed above, each participant was selected to complete five groups of experiments. The estimated time for completion of the five groups (incorporating nineteen experiments) was approximately ninety minutes.

**Experiments protocol:** This section presents a practical overview in relation to the conducting of the battery of experiments for each participant.

- **Hardware and software set-up checks:** Generally speaking, on any one day there may be two to three participants scheduled to complete the AC experiments. Prior to each scheduled day, the hardware and software was taken through a test run to ensure all was working correctly. If any issues were identified they were rectified well in advance of the live experiments.
- **Participant welcome and briefing:** On the day of the experiments, the participant was met at reception and brought to the AC research

[17] http://www.isunet.edu/

laboratory. Once they were seated they were given a general overview of the hardware, software and the experiment process. As soon as possible they were fitted with the E4 wearable (discussed below). During this stage the participant read, completed and signed the experiment's consent form. The GEW self-reporting form was also explained to then along with the importance of the start and stop time reporting data on the form. Any questions were answered in relation to the GEW as required. The briefing process took between twenty to twenty five minutes and once all forms were completed and questions answered the final task was to let the participant choose the order of the experiment groups. The participant selected at random the delivery order from experiment group numbers 01, 02, 03, 04, and 06 (experiments group 05 was not conducted in this thesis research due to ethical concerns and other limitations).

- **Sensor calibration and servers:** As mentioned above, once the participant was seated and introduced to the set-up they were asked which hand they wrote with, this information indicated which hand was their non-dominant hand. The E4 was then fitted snugly on the wrist of their non-dominant hand. After this the E4 was launched and connected to the Empatica server. Once server connections were made successfully, the participant continued with the consent form and the rest of the briefing activities discussed above.
- **Management of experiments and self-reporting:** Each group of experiments followed a specific protocol. At the start of each experiment group the participant had to read and sign an overview document. They were also given the opportunity to ask any questions. In the case of the computer games based tasks the participant was given a quick one minute

demonstration of each task by the researcher. For all other experiments, no demonstration or lead in was provided. The researcher was responsible for ensuring that the participant completed the GEW self-report form for each experiment in the thematic group and also that the start and end times for each of the experiment's activities were recorded accurately. At the end of each group of experiments, the relevant dataset files were anonymised using the unique participant identity code and were saved locally and to cloud based backup resources.

- **Experiments wrap-up procedures:** As discussed, participants were given a short walk around break after the third experiment for five minutes. On completion of the five groups of experiments the hardware was turned off using the EFS server shutdown option. All anonymised dataset files were fully checked and backed up to external sources. The GEW forms for each of the nineteen experiments tasks along with the related experiment's overview/disclaimer forms were securely compiled for later processing to the self-reporting dataset. The E4 device was then hygienically cleaned and put on charge for the next participant. All artifacts used throughout the experiments were fully checked and reorganised for the next participant. Finally all of the documentation was double checked and placed in the order of presentation, formally signed off and dated by the researcher, and placed in a secure location.

That completes this comprehensive section on the overall design and organisation of the AC experiments conducted for the thesis research. The reader is again advised that all of the AC experiments documentation, with step by step detailed instructions for researchers, and the ethics approval submission documentation is contained in volume 2 of 2 of this thesis.

## 5.3 Experiments Data Sets

Firstly this section provides an overview of the datasets that were produced from the experiments that were conducted. This is then followed by examples relating to the EmotionViewer, EmpaticaEmotions and the GEW self-report datasets. Details of the datasets preparations and pre-processing are also provided.

**Overview of experiments data sets produced:** This section presents a brief overview of the datasets produced by the EFS for the statistical reporting and analytics phases of the research. In relation to the datasets produced, each of the nineteen experiments can be individually isolated and extracted from a specific dataset. The use of experiment groups can also be used to create unique thematic use case related datasets across the sample population if required.

The following outlines the three main datasets that have been produced from the experiments.

**EmotionViewer vision dataset:** This dataset was produced using the EFS EmotionViewer adaptor. The vision data captured (including emotion classification) using the Real Sense camera was directly fused with the wearable data in a CSV file for each experiment.

**EmpaticaEmotions wearables dataset:** This dataset was produced using the EFS EmpaticaEmotions adaptor. The wearables data captured using the Empatica E4 was also directly fused with the vision data in a CSV file for each experiment. The EmpaticaEmotions adaptor also produced extra files that captured the raw sensor data feeds from the E4 device prior to processing by the EmpaticaEmotions adaptor. These files are available as a separate dataset if deeper analytics may be required in the future in relation to the sensor signals and their near real-time timestamp data.

**MAT dataset:** A separate MAT facial feature landmark dataset was also produced in conjunction with SIGMA researcher Michael Healy in relation to his specific AC vision research project. Please note that this dataset is not discussed any further in this section.

**GEW self-report dataset:** As each of the experiments were completed the participant filled out the GEW self-report form. Each participant completed a total of nineteen GEW forms throughout the experiments. All of the forms were then entered into a purpose designed spreadsheet with the capture of temporal data and the user analysis of the emotions they experienced during the tasks in the various experiments. The dataset also included an intensity value for a maximum of three emotions experienced by the participant as they completed each of the nineteen experiments.

The datasets captured are now described in further technical detail in the next section where sample extracts from the above datasets will be discussed along with an explanation of all relevant data features.

**EmotionViewer (EV) dataset extract:** The Figure 5-1 EmotionViewer (EV) Dataset Extract is from the vision depth camera using the EmotionViewer adaptor performing emotion classifications.

| Emotion | Sentiment | Occurrence | Intensity | Evidence | Timestamp |
|---|---|---|---|---|---|
| CONTEMPT | POSITIVE | 11 | 0.332192 | 0 | 12:13:14 |
| CONTEMPT | POSITIVE | 29 | 0.395799 | 0 | 12:13:15 |
| CONTEMPT | NEUTRAL⍰ | 20 | 0.409480 | 0 | 12:13:16 |
| SADNESS | NEUTRAL⍰ | 20 | 0.102582 | 0 | 12:13:17 |
| CONTEMPT | NEUTRAL⍰ | 13 | 0.064287 | 0 | 12:13:18 |
| SADNESS | NEUTRAL⍰ | 27 | 0.096315 | 0 | 12:13:19 |
| ANGER⍰ | NEUTRAL⍰ | 28 | 0.106619 | 0 | 12:13:20 |
| SADNESS | NEUTRAL⍰ | 29 | 0.180046 | 0 | 12:13:21 |
| SADNESS | NEUTRAL⍰ | 17 | 0.298419 | 0 | 12:13:22 |
| ANGER⍰ | NEUTRAL⍰ | 31 | 0.346359 | 0 | 12:13:23 |
| SADNESS | NEGATIVE | 28 | 0.349720 | 0 | 12:13:24 |
| SADNESS | NEGATIVE | 30 | 0.360011 | 0 | 12:13:25 |
| SADNESS | NEUTRAL⍰ | 30 | 0.360368 | 0 | 12:13:26 |
| DISGUST | NEUTRAL⍰ | 23 | 0.048629 | 0 | 12:13:27 |
| DISGUST | NEGATIVE | 22 | 0.098865 | 0 | 12:13:28 |

**Figure 5-1 EmotionViewer (EV) Dataset Extract**

**EmotionViewer feature headings:**

- **Emotion:** One of seven emotion labels. *Contempt, Fear, Anger, Surprise, Disgust, Joy, and Sadness.*
- **Sentiment:** One of three labels. *Positive, Neutral, and Negative.*
- **Occurrence:** The number of occurrences of the most dominant emotion based on the timestamp interval.
- **Intensity:** Intensity of the emotion averages based on the occurrence value. Between 0 and 1.
- **Evidence:** Value between -5 and +5.
- **Timestamp:** Timestamps captured by the EmotionViewer sensor adaptor sent to the EFS.

**EmpaticaEmotions (EE) dataset extract:** The Figure 5-2 EmpaticaEmotions (EE) Dataset Extract is from the wearable wrist sensor (Empatica E4) using the EmpaticaEmotions adaptor providing the processed sensor values below.

| E4_gsrX | E4_hrX | E4_ibiX | E4_temperatureX | E4_TimeStamp | TimeStamp |
|---|---|---|---|---|---|
| 0.785781 | 74.623001 | 0.828163 | 32.344837 | 1501758789.295950 | 12:13:13 |
| 0.783272 | 74.845558 | 0.812537 | 32.335716 | 1501758793.618000 | 12:13:14 |
| 0.783272 | 72.449516 | 0.816444 | 32.335716 | 1501758791.733560 | 12:13:15 |
| 0.770184 | 72.449516 | 0.816444 | 32.335716 | 1501758795.118000 | 12:13:16 |
| 0.780432 | 72.449516 | 0.816444 | 32.338005 | 1501758796.618000 | 12:13:17 |
| 0.841917 | 72.449516 | 0.816444 | 32.330002 | 1501758797.368000 | 12:13:19 |
| 0.836473 | 72.449516 | 0.816444 | 32.330002 | 1501758798.118000 | 12:13:19 |
| 0.827570 | 72.449516 | 0.816444 | 32.318569 | 1501758799.618000 | 12:13:20 |
| 0.826429 | 72.449516 | 0.816444 | 32.318569 | 1501758799.868000 | 12:13:22 |
| 0.811430 | 72.449516 | 0.816444 | 32.318569 | 1501758801.118000 | 12:13:22 |
| 0.818091 | 72.449516 | 0.816444 | 32.319336 | 1501758802.618000 | 12:13:23 |
| 0.819287 | 77.073952 | 0.800037 | 32.330002 | 1501758802.868000 | 12:13:25 |
| 0.822190 | 78.615425 | 0.789099 | 32.330002 | 1501758801.030860 | 12:13:25 |
| 0.815367 | 83.474442 | 0.771520 | 32.331341 | 1501758802.468430 | 12:13:27 |
| 0.815367 | 78.363762 | 0.770869 | 32.331341 | 1501758803.234090 | 12:13:27 |
| 0.797084 | 76.827217 | 0.773473 | 32.335224 | 1501758804.031000 | 12:13:28 |
| 0.792077 | 74.920769 | 0.779865 | 32.335224 | 1501758808.618000 | 12:13:29 |

**Figure 5-2 EmpaticaEmotions (EE) Dataset Extract**

**EmpaticaEmotions feature headings:**

- **E4_gsrX:** Mean value of the E4 GSR sensor values.
- **E4_hrX:** Mean value of the E4 processed heart rate values.
- **E4_ibiX:** Mean value of the E4 processed heart inter beat interval values.
- **E4_temperatureX:** Mean value of the E4 processed body temperature values.
- **E4_TimeStamp:** Microsecond timestamp data points captured directly from the E4 wearable device.
- **Timestamp:** Timestamps captured by the EmpaticaEmotions sensor adaptor sent to the EFS.

**GEW self-reporting dataset extract:** The GEW data set in Figure 5-3 Geneva Emotion Wheel (GEW) Self-Report Dataset Extract is produced from the subject's nineteen GEW self-report forms completed after each of the experiments.

| P-ID | Exp-ID | Experiment 01 Description | Date | Start Time | End Time |
|---|---|---|---|---|---|
| AC-018 | E01-A | ThinkGeek Box | 29 August 2017 | 13:05:30 | 13:07:34 |
| AC-018 | E01-B | Prof. Puzzle | 29 August 2017 | 13:08:09 | 13:08:57 |
| AC-018 | E01-C | Vaseline | 29 August 2017 | 13:09:20 | 13:09:51 |
| AC-018 | E01-D | Mouse Trap | 29 August 2017 | 13:10:12 | 13:11:22 |
| | | Experiment 02 Description | | | |
| AC-018 | E02-A | Negative recall | 29 August 2017 | 12:17:03 | 12:19:03 |
| AC-018 | E02-B | Positive recall | 29 August 2017 | 12:19:56 | 12:20:56 |
| AC-018 | E02-C | Any recall | 29 August 2017 | 12:21:38 | 12:22:40 |
| | | Experiment 03 Description | | | |
| AC-018 | E03-A | Video - Pippa | 29 August 2017 | 11:58:00 | 11:59:32 |
| AC-018 | E03-B | Images - Disgust | 29 August 2017 | 12:01:30 | 12:02:25 |
| AC-018 | E03-C | Images - Fear | 29 August 2017 | 12:03:10 | 12:04:00 |
| AC-018 | E03-D | Images - Sadness | 29 August 2017 | 12:04:35 | 12:05:35 |
| AC-018 | E03-E | Images - Relaxed/Content | 29 August 2017 | 12:06:10 | 12:07:00 |
| | | Experiment 04 Description | | | |
| AC-018 | E04-A | Baby powder | 29 August 2017 | 12:56:55 | 12:57:18 |
| AC-018 | E04-B | Deep Heat | 29 August 2017 | 12:57:37 | 12:58:00 |
| AC-018 | E04-C | Coconut bath bomb | 29 August 2017 | 12:58:20 | 12:58:45 |
| AC-018 | E04-D | Jeyes Fluid | 29 August 2017 | 12:59:00 | 12:59:20 |
| AC-018 | E04-E | Lavender | 29 August 2017 | 12:59:43 | 13:00:10 |
| | | Experiment 06 Description | | | |
| AC-018 | E06-A | Stroop Test - Pressure Game | 29 August 2017 | 12:39:55 | 12:43:07 |
| AC-018 | E06-B | Colour Reaction Test | 29 August 2017 | 12:48:11 | 12:50:27 |

**Figure 5-3 Geneva Emotion Wheel (GEW) Self-Report Dataset Extract**

**Explanation of the headings in the self-report Excel sheet:**

- **P-ID:** Unique identity number of participant taking the experiments.
- **Exp-ID:** Identity code for the experiment and its related thematic group. For example E03-C is the third experiment in group number three (E03).
- **Experiment Description:** This is a brief description with a full explanation of each experiment contained in the experiments appendices documentation.
- **Date:** Actual date when the experiments took place for the participant involved.
- **Start Time:** Start time for the experiment activity.

- **End Time:** End time for the experiment activity.

**GEW dataset extract of GEW emotions:** The Figure 5-4 Geneva Emotion Wheel (GEW) Emotions Part 1 and Figure 5-5 Geneva Emotion Wheel (GEW) Emotions Part 2 are extracted from the self-report dataset and shows all twenty emotions from the GEW and related intensity scores. A maximum of three emotions (including intensity scores) were recorded for each of the nineteen GEW experiment forms completed by each participant.

| Interest | Amusement | Pride | Joy | Pleasure | Contentment | Love | Admiration | Relief | Compassion |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |
| | | | | | | | | | |
| | | | | | | | | | |

**Figure 5-4 Geneva Emotion Wheel (GEW) Emotions Part 1**

| Sadness | Guilt | Regret | Shame | Disappointment | Fear | Disgust | Contempt | Hate | Anger |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 4 | | | |
| | | | | | | | | | 5 |
| | | | | | | | | | |
| | | | | | | | | | 4 |

**Figure 5-5 Geneva Emotion Wheel (GEW) Emotions Part 2**

The final parts of the dataset in Figure 5-6 Geneva Emotion Wheel (GEW) None or Other Emotions provided for the situation where the participant did not feel any emotion for an experiment activity and could thus mark **None** to indicate that no emotion was felt during the experiment. The green section provides for the listing of an emotion and its related intensity scale (1 – 5) if the emotion was not in the pre-defined set of twenty GEW emotions.

| None | Other Emotion Name | Other Emotion Scale | Notes |
|---|---|---|---|
| | | | |
| | | | |
| | Annoyance (Anger ?? ) | 3 | As written. |
| | | | |
| None | | | |

**Figure 5-6 Geneva Emotion Wheel (GEW) None or Other Emotions**

**Experiments dataset preparations and pre-processing:** Having outlined the datasets that were captured during the experiments, this section provides an overview of how the datasets were prepared for statistical processing and analysis purposes.

The following table in Figure 5-7 Experiments Summary synopsises the numbers of participants, experiments and datasets produced during the AC experiments phases.

| AC Experiments Datasets Overview | Totals | Vision - EmotionViewer | Wearable - EmpaticaEmotions | EFS Fusion | Raw Wearable Data | Self-Report |
|---|---|---|---|---|---|---|
| Total number of participants | 33 | | | | | |
| Total number of AC experiments per participant | 19 | | | | | |
| Total number of experiments in Group #1 - Dexterity | 132 | √ | √ | √ | √ | √ |
| Total number of experiments in Group #2 - Cognitive recall | 99 | √ | √ | √ | √ | √ |
| Total number of experiments in Group #3 - Imagery | 165 | √ | √ | √ | √ | √ |
| Total number of experiments in Group #4 - Olfactory | 165 | √ | √ | √ | √ | √ |
| Total number of experiments in Group #6 - Computer tasks | 66 | √ | √ | √ | √ | √ |
| **Total number of experiments across all participants** | 627 | √ | √ | √ | √ | √ |

**Figure 5-7 Experiments Summary**

The table summarises the total number of experiments that were conducted across the thirty three participants that signed up to participate in the research. The data produced can also be uniquely separated into both vision and wearable datasets if required for research purposes. The EFS produced a fusion based dataset that combines the EmotionViewer vision and the EmpaticaEmotions wearable data captured together into one CSV file.

Also in the above table, note that there is also a dataset called Raw Wearable Data captured during the experiments. This is a by-product of the wearables adaptor and has also been captured as it gives millisecond sensor related data from the Empatica E4. This provides for a drill down facility into a specific sensor value if required and also this raw sensor dataset can be used for additional research as further advancement of this thesis research in the future. The self-report datasets relate to the paper based GEW forms that were produced by the participants as they worked through each group of experiments.

**Experiment sensor datasets preparation:** The sensor datasets represented in the above table provide an insight into the totality of the sensor data that was captured by the EFS. In terms of data preparation, the main focus was on the fused CSV file produced for each group of experiments.

For logistical and experiment flow reasons, it was decided to set up the EFS system to capture all of the sensor data (vision and wearable) into a unique CSV file for each thematic group of experiments completed by the participant. For example for the dexterity group of experiments, the EFS produced one CSV file that fused both the vision and wearable data together on a per second basis for all of the four experiments in the group. Thus for each participant, the main outputs from the EFS were five CSV files (relating to each thematic group of experiments) that indirectly contained the fused sensor data for all of the nineteen experiments conducted. These five CSV files were then stored for each participant into a secure data repository under a unique identity code. It is from these CSV files, separate vision and wearable datasets may be produced as required for research purposes. Also as discussed above, the raw millisecond wearable data was also produced and this was stored in a separate data repository.

**Experiment sensor datasets pre-processing:** The five group based CSV files are the fundamental AC experiments outputs produced for each participant. As the participant worked through each experiment in the group there was noise data relating to the researcher in the room and around the computer, time taken up when the participant was self-reporting and also just general organisation activity of the participant and the researcher. All of this noise, picked up by the sensors had to be extracted in order to create the pure data relating to the actual experiments conducted by the participant.

The sensor datasets required pre-processing to remove all noise related artifacts picked up, other than the data relating to the nineteen experiments. Considering that each EFS produced CSV file contained a number of experiments, it was required to extract time sliced data as close as possible to the time when the participant was actually performing the experiments.

In order to extract the time-sliced data, the self-report GEW forms were used. This involved taking the self-report forms for each group of experiments completed and using the recorded start and stop times to extract the specific data relating to the experiment duration. The completion of this task for each participant that completed all experiments resulted in a total of nineteen time sliced datasets for each participant.

Having extracted the time sliced sensor datasets for each experiment, they were than all compiled into individual experiment group folders as represented in the Figure 5-8 Experiment Group E01 - Sub-folders. This shows a number of sub-folders for all the experiments in group E01. These sub-folders contained the processed time sliced datasets for all the experiments across all thirty three participants. The group folders also contained the originals before time slicing actions.

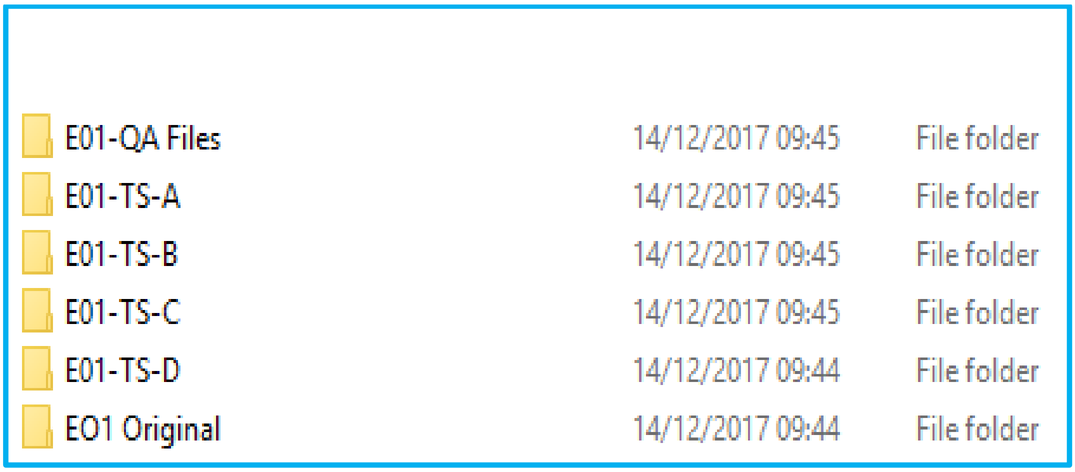


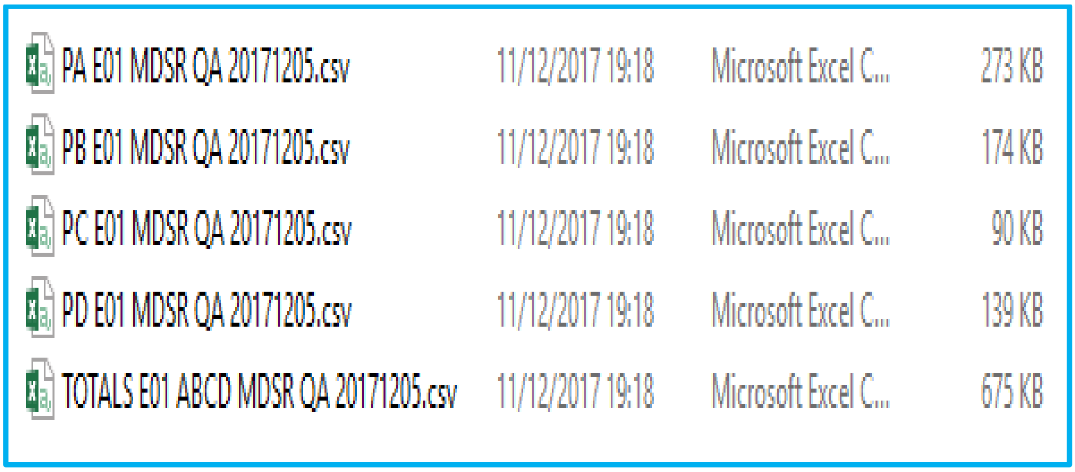

**Figure 5-8 Experiment Group E01 - Sub-folders**

As part of producing and organising all of the time sliced data for each experiment and their related grouping, there was a further quality control process applied to inspect the sensor data produced. Generally speaking this involved the manual inspection of the sensor reported data and eliminating any instances likely to corrupt the dataset. For example, the E4 sensor HR data stream was found to report zero values primarily at the very start of the monitoring period, any other sensors that reported a zero or unusual values were also deleted from the dataset in question. As part of the control process, when sensor data was identified as being corrupt in any way, the full data observation (feature vector/sample) was fully removed from the quality assured (QA) dataset.

As an example, the Figure 5-9 Experiment Group E01 Quality Assured (QA) Files screen shot shows the compiled master files for the four experiments (PA to PD) contained in the experiment group E01. The last file TOTALS E01 ABCD MDSR QA 20171205.csv compiles all the sensor data from the four experiments PA to

PD. So with reference to the example dexterity group of experiments (E01) it is possible to produce reporting and analytics across:

- Full group of participants for a specific experiment (1 to 19).
- Full group of participants for all experiments in a specific thematic group.
- Full group of participants for all experiments in all thematic groups.
- Single participant across specific experiments in a specific thematic group.
- Single participant across all experiments across all thematic groups.
- Selected group of participants across experiments and thematic groups as required.



| | | | |
|---|---|---|---|
| PA E01 MDSR QA 20171205.csv | 11/12/2017 19:18 | Microsoft Excel C... | 273 KB |
| PB E01 MDSR QA 20171205.csv | 11/12/2017 19:18 | Microsoft Excel C... | 174 KB |
| PC E01 MDSR QA 20171205.csv | 11/12/2017 19:18 | Microsoft Excel C... | 90 KB |
| PD E01 MDSR QA 20171205.csv | 11/12/2017 19:18 | Microsoft Excel C... | 139 KB |
| TOTALS E01 ABCD MDSR QA 20171205.csv | 11/12/2017 19:18 | Microsoft Excel C... | 675 KB |

**Figure 5-9 Experiment Group E01 Quality Assured (QA) Files**

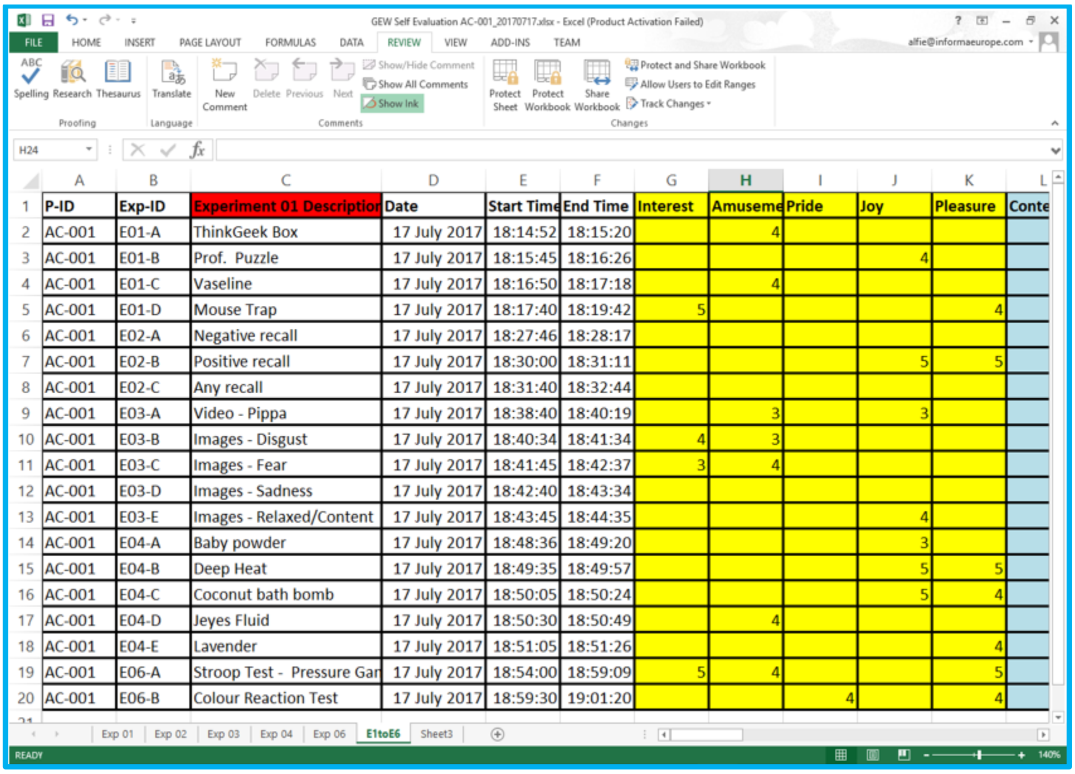
Once all of the quality assured time sliced data was compiled for each experiment across all five groups then a total master dataset was produced containing the fused sensor results for each of the nineteen experiments for all thirty three participants. This total master dataset was a compilation of the time sliced data into one extremely large dataset for the statistical reporting and analysis phases of the research.

**Experiment self-report datasets preparation:** As discussed, a GEW form was completed for each experiment completed by participants. This produced a total of nineteen forms for each participant. For each participant, the forms were checked at the end of the experiments and saved securely. The forms were then entered into a specially designed spreadsheet that captured the self-report data.

The spreadsheet has a tab for each of the experiment groups E01 to E06. Each line in each of the experiment group tabs captured the data from the GEW forms. This provided the start and stop time of the experiment. This critical data was used for the time slicing pre-processing discussed above. The unique participant identity, experiment identity code and date was also captured. The twenty emotions from the GEW form were listed and the intensity levels felt by the participant for the specific experiments were recorded. It was also noted if the participant did not feel any emotion or if they felt an emotion not contained in the GEW.

The screen shot in Figure 5-10 Self-reporting All Experiments for AC-001 shows the five tabs that contain the self-report data from all of the nineteen GEW forms. The tab on the far right is shown in the screen shot, which shows the lines entered from each form for AC-001. A similar spreadsheet was produced for all of the thirty three participants. As the forms were being entered for each participant there was a double quality assurance check made on the entered data. If there was any missing data due to a mistake by the participant then an informed best guess was made and entered by the researcher. This was also noted on the self-report form by the researcher if applicable.

**Experiment self-report datasets pre-processing:** The previous section has described how all of the paper based forms were prepared and entered into an Excel sheet for each participant based on the groups of experiments. All of the self-report data was also compiled into a master view sheet that showed all of the nineteen experiments completed by the participant.

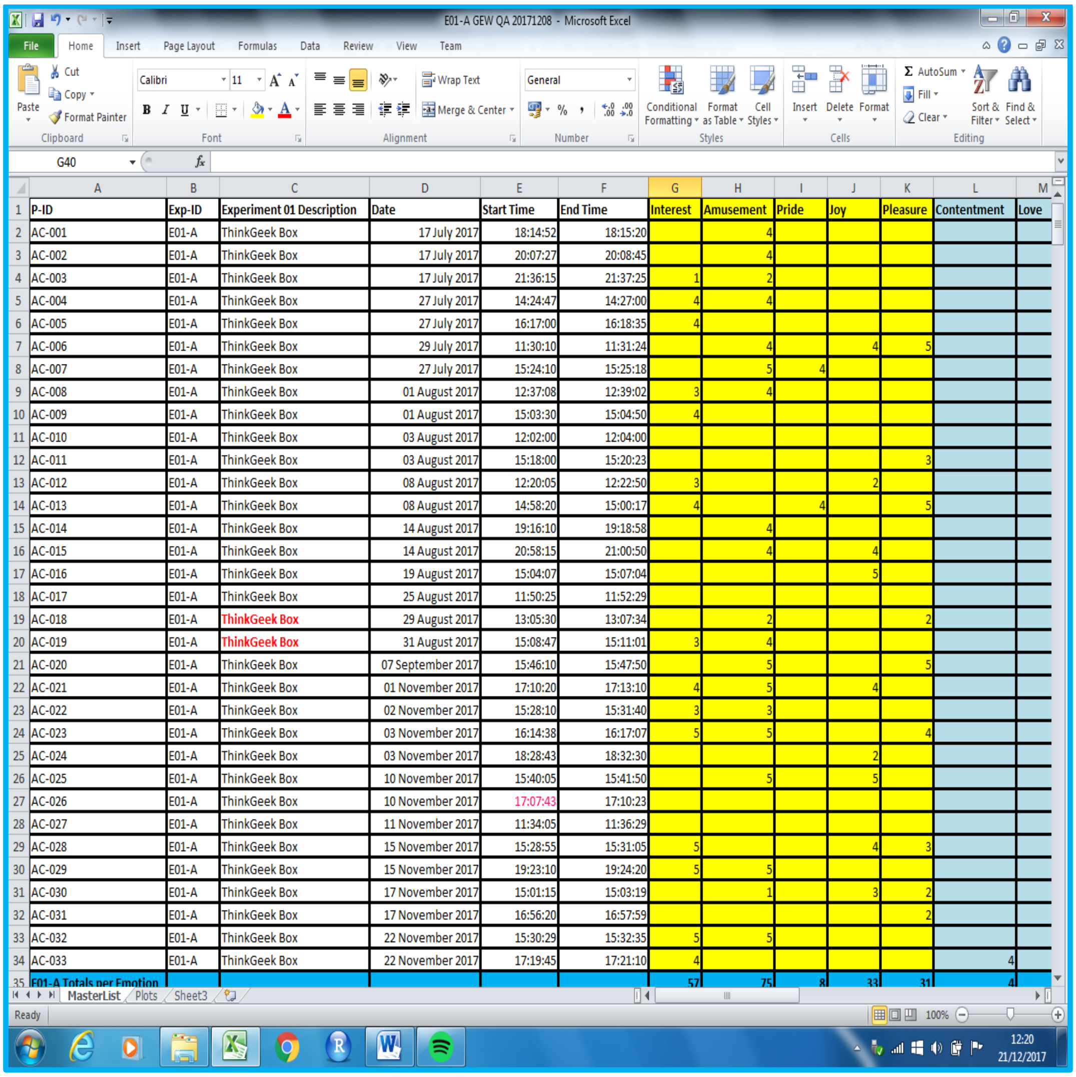


| P-ID | Exp-ID | Experiment 01 Descriptior | Date | Start Time | End Time | Interest | Amuseme | Pride | Joy | Pleasure | Conte |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AC-001 | E01-A | ThinkGeek Box | 17 July 2017 | 18:14:52 | 18:15:20 | | 4 | | | | |
| AC-001 | E01-B | Prof. Puzzle | 17 July 2017 | 18:15:45 | 18:16:26 | | | | 4 | | |
| AC-001 | E01-C | Vaseline | 17 July 2017 | 18:16:50 | 18:17:18 | | 4 | | | | |
| AC-001 | E01-D | Mouse Trap | 17 July 2017 | 18:17:40 | 18:19:42 | 5 | | | | 4 | |
| AC-001 | E02-A | Negative recall | 17 July 2017 | 18:27:46 | 18:28:17 | | | | | | |
| AC-001 | E02-B | Positive recall | 17 July 2017 | 18:30:00 | 18:31:11 | | | | 5 | 5 | |
| AC-001 | E02-C | Any recall | 17 July 2017 | 18:31:40 | 18:32:44 | | | | | | |
| AC-001 | E03-A | Video - Pippa | 17 July 2017 | 18:38:40 | 18:40:19 | | 3 | | 3 | | |
| AC-001 | E03-B | Images - Disgust | 17 July 2017 | 18:40:34 | 18:41:34 | 4 | 3 | | | | |
| AC-001 | E03-C | Images - Fear | 17 July 2017 | 18:41:45 | 18:42:37 | 3 | 4 | | | | |
| AC-001 | E03-D | Images - Sadness | 17 July 2017 | 18:42:40 | 18:43:34 | | | | | | |
| AC-001 | E03-E | Images - Relaxed/Content | 17 July 2017 | 18:43:45 | 18:44:35 | | | | 4 | | |
| AC-001 | E04-A | Baby powder | 17 July 2017 | 18:48:36 | 18:49:20 | | | | 3 | | |
| AC-001 | E04-B | Deep Heat | 17 July 2017 | 18:49:35 | 18:49:57 | | | | 5 | 5 | |
| AC-001 | E04-C | Coconut bath bomb | 17 July 2017 | 18:50:05 | 18:50:24 | | | | 5 | 4 | |
| AC-001 | E04-D | Jeyes Fluid | 17 July 2017 | 18:50:30 | 18:50:49 | | 4 | | | | |
| AC-001 | E04-E | Lavender | 17 July 2017 | 18:51:05 | 18:51:26 | | | | | 4 | |
| AC-001 | E06-A | Stroop Test - Pressure Gar | 17 July 2017 | 18:54:00 | 18:59:09 | 5 | 4 | | | 5 | |
| AC-001 | E06-B | Colour Reaction Test | 17 July 2017 | 18:59:30 | 19:01:20 | | | 4 | | 4 | |

**Figure 5-10 Self-reporting All Experiments for AC-001**

The next phase of preparing the GEW data was to be able to look at all of the self-report data results for all participants for an individual experiment or indeed a group of experiments. This data pre-processing involved extracting all of the responses provided by participants for each of the experiments they completed. This created nineteen Excel sheets with each sheet containing views of the self-reporting for all thirty three participants. The Figure 5-11 Experiment Group E01 Self-reporting Data screen shot presents a view of the self-report data for the first experiment in the dexterity group (E01-A) for all of the participants.

Once the sheets were compiled for each experiment in a group, it was then possible to create a GEW totals master sheet for all of the experiments in a group. As discussed already, each participant was given an option to report an emotion even if it was not contained in the GEW. As part of the data pre-processing, decisions had to be made as to how emotions outside of the GEW twenty were entered. When an outside emotion was written down by a participant it was also recorded in the Excel sheet. As part of the quality assurance of the GEW data, the outside emotion was matched to an existing emotion from the GEW list wherever possible. Unless the person wrote down an emotional scale on the form a value of five was entered due to the fact the emotion was foremost in their cognitive thought process. The decision made on this pre-processing by the researcher was recorded in the spreadsheet where the query/decision occurred.



| | A | B | C | D | E | F | G | H | I | J | K | L | M |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | P-ID | Exp-ID | Experiment 01 Description | Date | Start Time | End Time | Interest | Amusement | Pride | Joy | Pleasure | Contentment | Love |
| 2 | AC-001 | E01-A | ThinkGeek Box | 17 July 2017 | 18:14:52 | 18:15:20 | | 4 | | | | | |
| 3 | AC-002 | E01-A | ThinkGeek Box | 17 July 2017 | 20:07:27 | 20:08:45 | | 4 | | | | | |
| 4 | AC-003 | E01-A | ThinkGeek Box | 17 July 2017 | 21:36:15 | 21:37:25 | 1 | 2 | | | | | |
| 5 | AC-004 | E01-A | ThinkGeek Box | 27 July 2017 | 14:24:47 | 14:27:00 | 4 | 4 | | | | | |
| 6 | AC-005 | E01-A | ThinkGeek Box | 27 July 2017 | 16:17:00 | 16:18:35 | 4 | | | | | | |
| 7 | AC-006 | E01-A | ThinkGeek Box | 29 July 2017 | 11:30:10 | 11:31:24 | | 4 | | 4 | 5 | | |
| 8 | AC-007 | E01-A | ThinkGeek Box | 27 July 2017 | 15:24:10 | 15:25:18 | | 5 | 4 | | | | |
| 9 | AC-008 | E01-A | ThinkGeek Box | 01 August 2017 | 12:37:08 | 12:39:02 | 3 | 4 | | | | | |
| 10 | AC-009 | E01-A | ThinkGeek Box | 01 August 2017 | 15:03:30 | 15:04:50 | 4 | | | | | | |
| 11 | AC-010 | E01-A | ThinkGeek Box | 03 August 2017 | 12:02:00 | 12:04:00 | | | | | | | |
| 12 | AC-011 | E01-A | ThinkGeek Box | 03 August 2017 | 15:18:00 | 15:20:23 | | | | | 3 | | |
| 13 | AC-012 | E01-A | ThinkGeek Box | 08 August 2017 | 12:20:05 | 12:22:50 | 3 | | | 2 | | | |
| 14 | AC-013 | E01-A | ThinkGeek Box | 08 August 2017 | 14:58:20 | 15:00:17 | 4 | | 4 | | 5 | | |
| 15 | AC-014 | E01-A | ThinkGeek Box | 14 August 2017 | 19:16:10 | 19:18:58 | | 4 | | | | | |
| 16 | AC-015 | E01-A | ThinkGeek Box | 14 August 2017 | 20:58:15 | 21:00:50 | | 4 | | 4 | | | |
| 17 | AC-016 | E01-A | ThinkGeek Box | 19 August 2017 | 15:04:07 | 15:07:04 | | | | 5 | | | |
| 18 | AC-017 | E01-A | ThinkGeek Box | 25 August 2017 | 11:50:25 | 11:52:29 | | | | | | | |
| 19 | AC-018 | E01-A | ThinkGeek Box | 29 August 2017 | 13:05:30 | 13:07:34 | | 2 | | | 2 | | |
| 20 | AC-019 | E01-A | ThinkGeek Box | 31 August 2017 | 15:08:47 | 15:11:01 | 3 | 4 | | | | | |
| 21 | AC-020 | E01-A | ThinkGeek Box | 07 September 2017 | 15:46:10 | 15:47:50 | | 5 | | | 5 | | |
| 22 | AC-021 | E01-A | ThinkGeek Box | 01 November 2017 | 17:10:20 | 17:13:10 | 4 | 5 | | 4 | | | |
| 23 | AC-022 | E01-A | ThinkGeek Box | 02 November 2017 | 15:28:10 | 15:31:40 | 3 | 3 | | | | | |
| 24 | AC-023 | E01-A | ThinkGeek Box | 03 November 2017 | 16:14:38 | 16:17:07 | 5 | 5 | | | 4 | | |
| 25 | AC-024 | E01-A | ThinkGeek Box | 03 November 2017 | 18:28:43 | 18:32:30 | | | | 2 | | | |
| 26 | AC-025 | E01-A | ThinkGeek Box | 10 November 2017 | 15:40:05 | 15:41:50 | | 5 | | 5 | | | |
| 27 | AC-026 | E01-A | ThinkGeek Box | 10 November 2017 | 17:07:43 | 17:10:23 | | | | | | | |
| 28 | AC-027 | E01-A | ThinkGeek Box | 11 November 2017 | 11:34:05 | 11:36:29 | | | | | | | |
| 29 | AC-028 | E01-A | ThinkGeek Box | 15 November 2017 | 15:28:55 | 15:31:05 | 5 | | | 4 | 3 | | |
| 30 | AC-029 | E01-A | ThinkGeek Box | 15 November 2017 | 19:23:10 | 19:24:20 | 5 | 5 | | | | | |
| 31 | AC-030 | E01-A | ThinkGeek Box | 17 November 2017 | 15:01:15 | 15:03:19 | | 1 | | 3 | 2 | | |
| 32 | AC-031 | E01-A | ThinkGeek Box | 17 November 2017 | 16:56:20 | 16:57:59 | | | | | 2 | | |
| 33 | AC-032 | E01-A | ThinkGeek Box | 22 November 2017 | 15:30:29 | 15:32:35 | 5 | 5 | | | | | |
| 34 | AC-033 | E01-A | ThinkGeek Box | 22 November 2017 | 17:19:45 | 17:21:10 | 4 | | | | | 4 | |
| 35 | E01-A Totals per Emotion | | | | | | 57 | 75 | 8 | 33 | 31 | 4 | |

**Figure 5-11 Experiment Group E01 Self-reporting Data**

The pre-processing and compilation of the GEW self-report data provides for reporting and analysis of:

- All participants for one or more experiments.
- All participants across one of more experiment thematic groups.
- All participants across all experiments.
- Specific participant across one or more experiments.
- Specific participant across one or more thematic groups of experiments.

After discussing the datasets preparations and the pre-processing involved, the next four sections of chapter five present statistical reporting, analysis, findings and conclusions in relation to the various datasets that have resulted from the AC research experiment phases.

## 5.4 Macro Statistical Evaluation: Hypothesis Reporting and Analysis

This section presents discussion and analysis of the statistical reporting and results that were produced from the experiments datasets with a specific focus at a macro level across a number of classification tracks. Due to the scale of the reporting that was conducted at both the macro and micro levels, only selected figures and tables will be provided in the remaining sections of this chapter.

As all statistical reporting and analysis figures are not provided in this chapter, the reader is advised to refer to the relevant statistical reporting appendices documents contained in the thesis volume 2 of 2 when reading the remaining sections of this chapter.

As a reference and reminder for the reader, the following look up Table 5-1 Experiment Codes and Overview Descriptions provides a summary of the various experiment group codes and their related individual experiment codes that will be used extensively as shorthand in the analytical discussions throughout the remaining sections of chapter five.

| Group | Experiment | Description |
|---|---|---|
| **E01** | | **Experiments group E01 dexterity based object interactions** |
| | **E01-PA** | Puzzle - Experiment to open a box puzzle object |
| | **E01-PB** | Puzzle - Experiment to separate two metal rings or to put them together |
| | **E01-PC** | Slippery object - Opening of a slippery tin of Vaseline |
| | **E01-PD** | Mouse trap - Setting and activation of a mouse trap |
| **E02** | | **Experiments group E02 cognitive based** |
| | **E02-PA** | Cognitive recall - Negative emotional experience |
| | **E02-PB** | Cognitive recall - Positive emotional experience |
| | **E02-PC** | Cognitive recall - Positive or Negative emotional experience |
| **E03** | | **Experiments group E03 visual based** |
| | **E03-PA** | Video - Pippa the cat who got its head stuck in a tissue box |
| | **E03-PB** | Images - Still images of Disgust |
| | **E03-PC** | Images - Still images of Fear |
| | **E03-PD** | Images - Still images of Sadness |
| | **E03-PE** | Images - Still images of Relaxation, Contentment, Joy |
| **E04** | | **Experiments group E04 olfactory based** |
| | **E04-PA** | Smell - Baby powder |
| | **E04-PB** | Smell - Deep Heat muscle strain cream |

| | | |
|---|---|---|
| | **E04-PC** | Smell - Coconut bath bomb |
| | **E04-PD** | Smell - Jeyes Fluid drain cleaner |
| | **E04-PE** | Smell - Lavender and Patchouli soap |
| **E06** | | **Experiments group E06 gaming based** |
| | **E06-PA** | Computer game - Stroop based game under time pressure |
| | **E06-PB** | Computer game - Speed reaction test |

**Table 5-1 Experiment Codes and Overview Descriptions**

### 5.4.1 Macro Bar Plots of Classification Possibilities

This section presents a number of bar plots that provide an overview of the total master dataset based on the classification possibilities that were used for the macro and micro statistical reporting and analysis. In addition to the explanations already presented previously, the experiments total master dataset was further transformed with the addition of participant IDs (ID), experiment groups (ExpGroup) and experiment IDs (ExpID). This additional encoding was conducted on the QA experiments total master dataset that has been discussed in the previous sections.

**Emotions (Emotion) classified bar plot:** The bar plot Figure 5-12 Totals for Emotions Classified provides results on the total number of emotion classification observations made by the EFS EmotionViewer adaptor. Notice that across the sample population the emotions of Fear and Surprise have very low classification numbers.

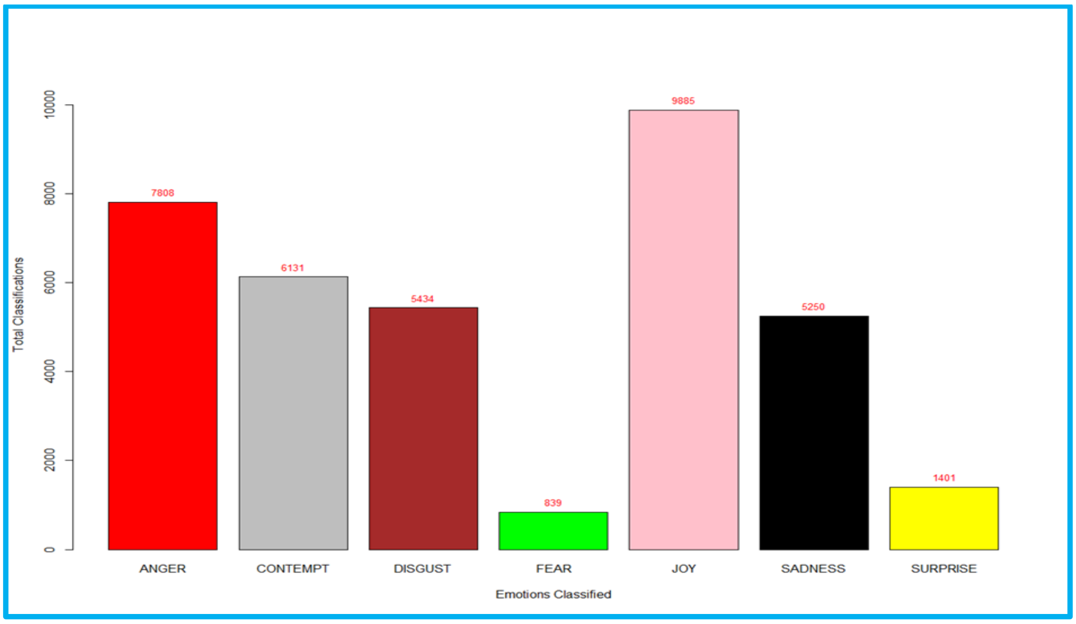



**Figure 5-12 Totals for Emotions Classified**

**Experiment groups (ExpGroup) classified bar plot:** The Figure 5-13 Totals for Experiment Groups Classified bar plot provides the total number of data observations per experiment group that were captured by the EFS platform for the sample population. Note that the samples here are related to the QA time sliced data that was extracted from the original EFS CSV files.

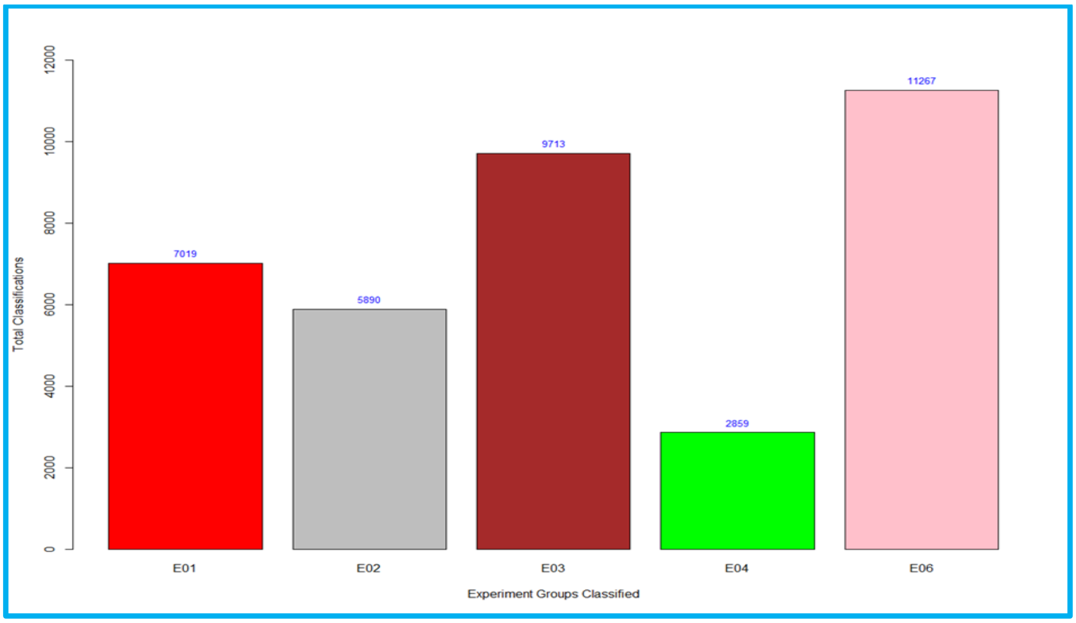



**Figure 5-13 Totals for Experiment Groups Classified**

A total of 36,748 data samples are represented across the above five experiment groups. E06 has the largest number as it took the longest time while E04 was rightly the shortest group containing a number of rapid olfactory based experiments.

**Individual experiment IDs (ExpID) classified bar plot:** The Figure 5-14 Totals for Experiment IDs Classified bar plot shows all of the nineteen experiments across the above five groups with the number of observations of each recorded by the EFS.

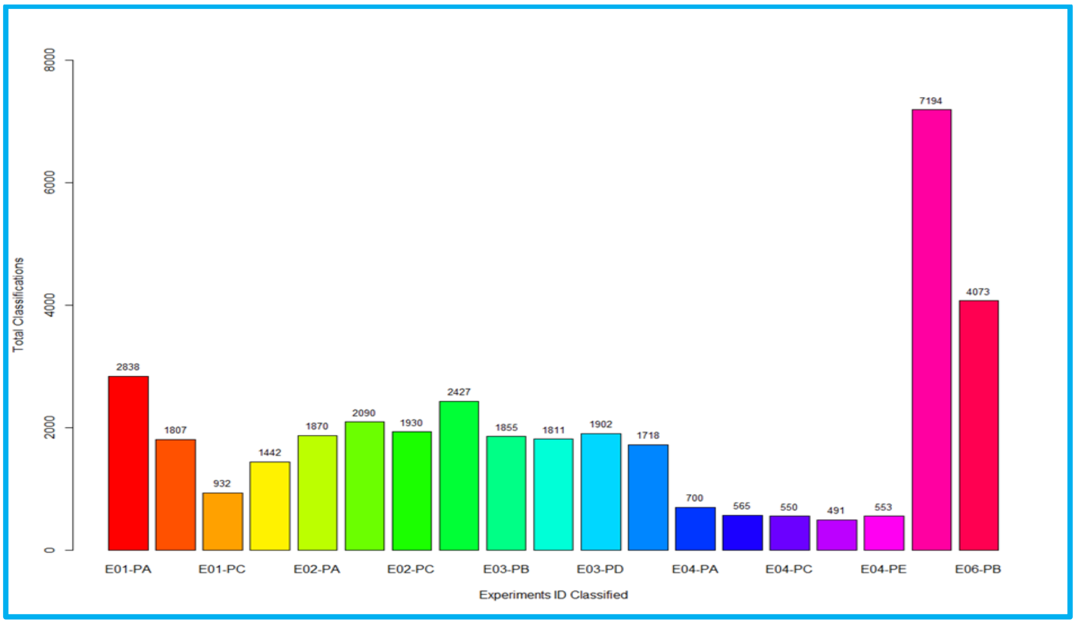



**Figure 5-14 Totals for Experiment IDs Classified**

**Individual participant IDs (ID) classified bar plot:** The Figure 5-15 Totals for Participant IDs Classified bar plot below shows all thirty three participants and the total number of data samples/observations recorded under their unique participant identity (ID).

This section provided macro reporting and analysis relating to the four types of classifications that have been investigated across the total master experiments dataset. These classifications will now be referenced extensively throughout the remaining sections of chapter five.

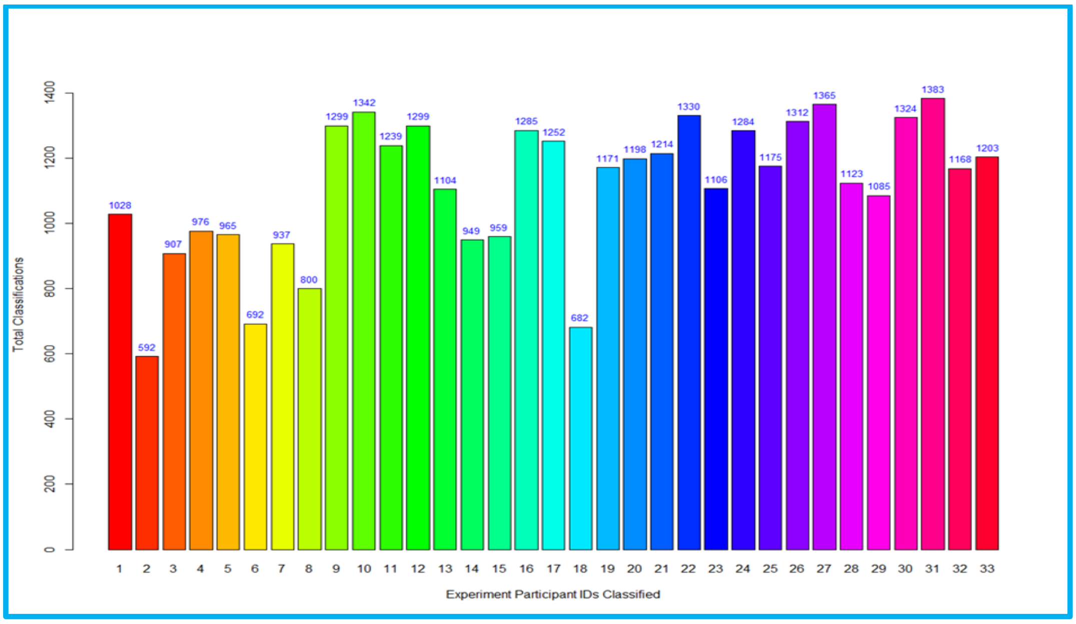



**Figure 5-15 Totals for Participant IDs Classified**

### 5.4.2 Macro Histograms for Sensor Data Streams

This section presents reporting and analysis using the classifications discussed above in relation to the wearable E4 sensor data streams. The Figure 5-16 Group E4 Sensor Statistics Macro Analysis provides overall summary statistics from all of the four wearable sensor features from the experiments total master dataset. Due to the variance in the GSR data and the lack of a normal distribution it was decided to get the log of the GSR data stream. This will be referred to as Log GSR data and will be discussed later as appropriate.

| Group E4 Sensor Statistics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Sensor Type** | **Min** | **1st Qu.** | **Median** | **Mean** | **3rd Qu.** | **Max.** | **IQR** | **Variance** | **SD** |
| GSR Sensor data | 0.0077 | 0.2121 | 0.3846 | 1.1715 | 0.9148 | 18.3659 | 0.7027 | 4.3070 | 2.0753 |
| HR Sensor data | 35.8862 | 64.0321 | 72.4495 | 71.9114 | 78.3638 | 153.5930 | 14.3317 | 151.1179 | 12.2930 |
| IBI Sensor data | 0.5313 | 0.7821 | 0.8261 | 0.8561 | 0.9061 | 1.5626 | 0.1240 | 0.0162 | 0.1272 |
| Temperature Sensor data | 29.0300 | 30.7897 | 32.2614 | 32.2333 | 33.2614 | 36.8153 | 2.4718 | 2.6016 | 1.6130 |
| | | | | | | | | | |
| **Log GSR** | -4.8684 | -1.5505 | -0.9557 | -0.7704 | -0.0890 | 2.9105 | 1.4615 | 1.7560 | 1.3251 |

**Figure 5-16 Group E4 Sensor Statistics Macro Analysis**

**GSR and Log GSR:** The raw GSR sensor first and third quartiles range from 0.21 to 0.91 across all of the experiments. For the log GSR this was from -1.55 to -0.08 for the respective quartiles.

**HR:** Within the first and third quartiles there is variation across the sample with the IQR at 14.33. The outlier of 153.59 was recorded and was validated with the E4 raw sensor data and has remained in the total dataset.

**IBI:** The IBI is negatively correlated with the HR sensor data and is separately computed from the E4 PPG data. The IBI first quartile is 0.78 and the third quartile is 0.90.

**Temperature:** This sensor shows first and third quartiles of 30.78 and 33.26. The mean temperature for the sample is 32.23.

Overall from the statistics of the above sensors across the total group sample the surprises are the outliers for the GSR and the HR. These maximum values show a large gap from their third quartiles. Temperature provides the least outliers in terms of data variation.

Histogram analysis of the normal GSR data shows 25,000+ data samples all within the range of zero to one microSiemens. The GSR sensor data then has a sudden drop to approximately 2,500 samples with values between 1 and 2. Thus the direct GSR data variation is primarily micro changes between 0 and 1. Using the transformed log GSR data there is a more natural spread of the data from -4 to 2. The Figure 5-17 Histogram Log Galvanic Skin Response (GSR) shows how the GSR data tends more toward a normal distribution rather than the original GSR sensor data stream values. As per the histogram below, the majority of the samples now exist between log GSR -2.5 and 0.5 values.

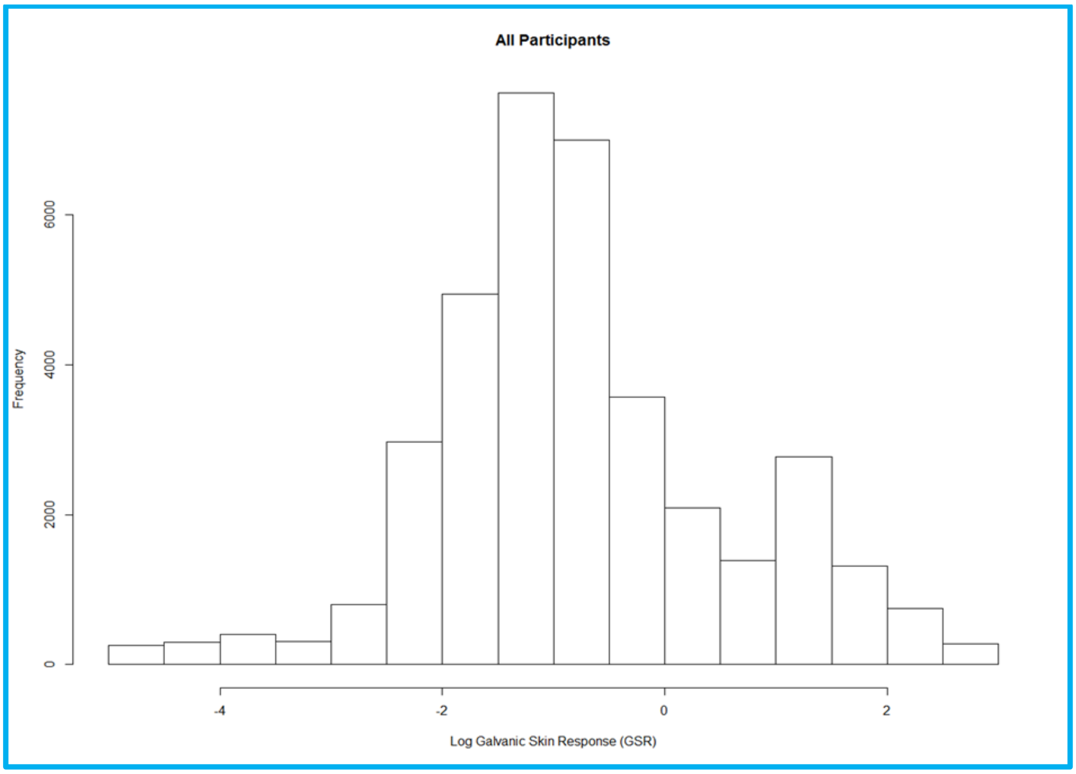



**Figure 5-17 Histogram Log Galvanic Skin Response (GSR)**

The HR shows a natural data distribution primarily from a HR of 45 to 100. Approximately 18,000+ data samples had a HR in the range of 65 to 80 according to the histogram from across the full sample. The IBI data also followed a similar natural distribution to the HR. The IBI range of most interest from 0.75 to 0.9 relates to approximately 22,000 samples. A number of outliers are also clearly identified in both histograms.

In the histogram data the temperature ranges from 30 to 36. Certain outliers have been identified that are lower than 30 and higher than 36. Approximately 13,500 samples lie in the range of 30 to 32, 12,500 in the range 32 to 34, and 7,000 in the range 34 to 36.

For reference purposes, the histogram plots discussed above are all available in the statistical appendices to the thesis in volume 2 of 2.

### 5.4.3 Macro Box Plots for Classification by Sensor Data Streams

This section presents reports and analysis at a macro level across the four classification groups presented in the previous section Macro Bar Plots of Classification. Each of the four classification sections present analysis and discussion in relation to the data observation for the E4 related data streams (GSR, Log GSR, HR, IBI and Temperature).

**Emotions (Emotion) by sensor, reporting and analysis:** The box plot of the emotion classification for the GSR shows minimum variance. Quite a number of outliers are also clearly identified across all of the seven emotions. Using the log of the GSR data values transformed the box plots. There is clear differentiation for the emotions minimum and maximum values and there are identifiable difference in their IQR and median values. The log GSR variances are clearly identified across Anger, Contempt and Disgust. Also there is variation identifiable in the Joy and Sadness emotion classifications. Fear and Surprise are of less interest due to the very low number of classification samples across the total dataset.

The HR data values do not reflect any major variance in the median values across the emotion classifications. The first quartile varies across Anger, Contempt and Disgust, while median values are extremely close. The third quartiles are also quite close in value across all seven emotions. Noticeably, the median HR for Sadness is higher than that of Joy and it has the highest median across all of the emotions classified. The IBI does not appear to add any additional insights to the emotion classifications. Taking the IBI medians for Joy and Sadness, the Joy median is actually higher than the Sadness median (opposite to the HR). Also the Disgust median is slightly under Anger, while Anger has a larger IQR than Disgust.

The box plots for temperature show interesting insights in relation to the emotion IQRs. Anger and Disgust appear to be very similar in terms of their IQR and their median values. Contempt shows the lowest median value (31.91) across all of the emotions classified. Taking Joy and Sadness, the median for Joy (32.42) is higher than that of Sadness (32.26). Also Sadness has a greater IQR range than Joy.

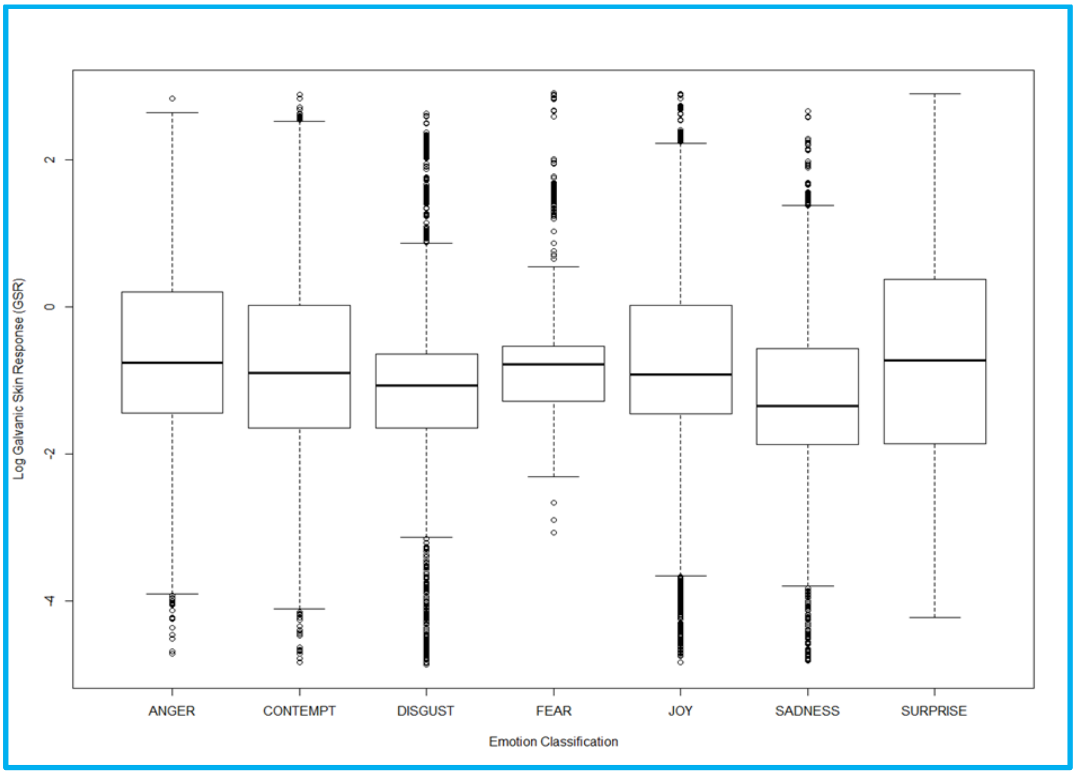



**Figure 5-18 Emotions by Log GSR Box Plot**

The Figure 5-18 Emotions by Log GSR Box Plot is one of five box plots produced for the emotion classification of the E4 sensor values. The Log GSR box plot demonstrates certain variance across the seven emotions that were identified by the EmotionViewer. The other emotion classification box plots are available in the statistical appendices documents of this thesis in volume 2 of 2.

**Experiment Groups (ExpGroup) by sensor, reporting and analysis:** This section provides reporting and analysis by each experiment group (ExpGroup) across all of the four wearable sensor feature data streams. The standard GSR shows no real variance across each experiment group and has considerable outliers for all groupings. The log GSR also shows significant outliers across all experiment groups. The log GSR medians are on a downwards trajectory for experiment groups E01 to E04. There is also variance in the IQRs data for these four groups, along with different minimum and maximum data ranges for each experiment group. The median is raised up for group E06 and is close in value to the median of E02.

For the HR data, the median and IQRs are very close for E01, E02 and E06. The medians and IQRs data for E03 and E04 are also quite close to each other. Minimum and maximum HR values are very close across all five groups. The main outliers are found in the E03 and E06 groups. The IBI results are naturally close with that of the HR box plots. E01, E02 and E06 have relatively close medians values. The medians for E03 and E04 are also close in value.

For skin temperature, the medians for E01, E02 and E06 are very similar. The first quartiles of all of the groups are very close in value. E01 and E03 have both got the highest third quartile and appear to be almost identical in value. While E01 and E03 have close IQRs, the median skin temperature of E03 (31.89) is considerably lower than that of E01 (32.36). In fact the E03 (imagery) group of experiments has the lowest skin temperature of all the experiment groups. The E04 olfactory group has the next lowest median skin temperature.

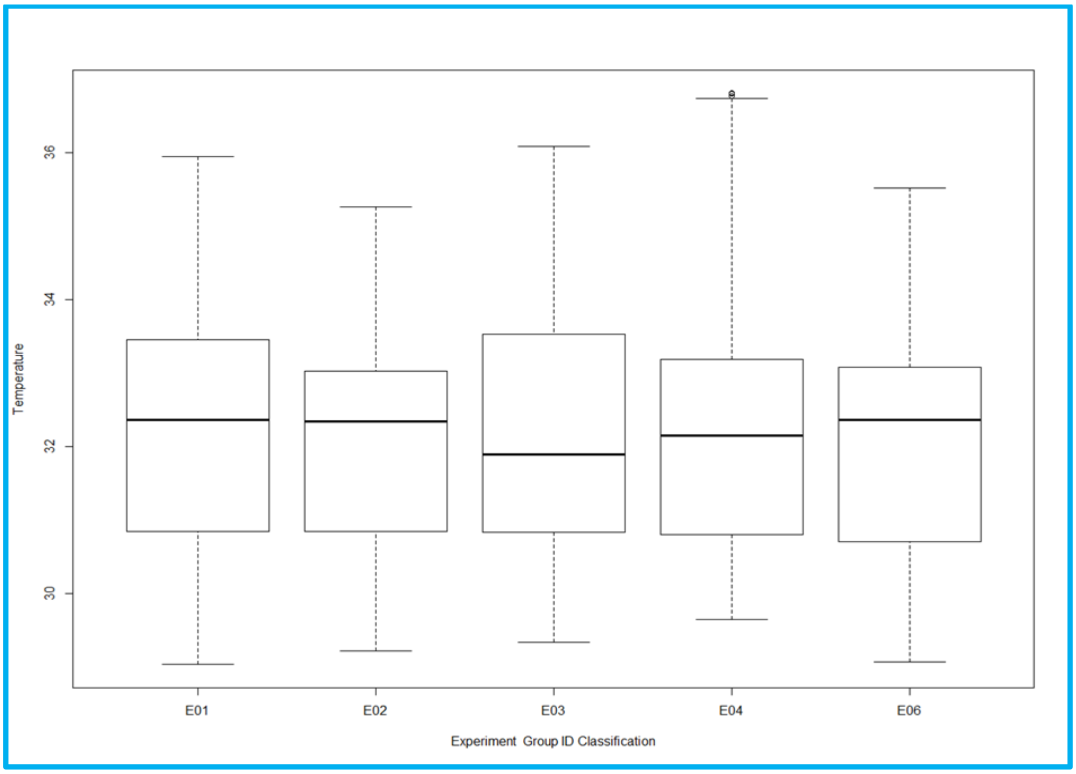



**Figure 5-19 Experiment Group by Temperature**

The Figure 5-19 Experiment Group by Temperature is one of five box plots produced for the experiment group classification of the E4 sensor values. The Temperature box plot clearly demonstrates that the E03 imagery group of experiments has an association with a drop in skin temperature across the population sample. The other emotion classification box plots are available in the statistical appendices documents of this thesis.

**Experiment IDs (ExpID) by sensor, reporting and analysis:** This section provides reporting and analysis across all of the nineteen AC experiments for all four sensor feature data streams. The normal GSR data values provided very little variance across experiments. There were fractional changes in the various medians in the box plots. Also considerable GSR outliers exist across the majority of the experiments. The log GSR provided a very different picture. This handled a lot of the outliers and also demonstrated certain levels of variance in the box plots for each of the experiments.

For E01 the log GSR is raised for the last two experiments on the Vaseline tin and the mouse trap. Also in E02 the first negative recall experiment produced a lower log GSR median than the next experiment on positive recall. For E03 on imagery experiments, the set of relaxed and contented images produced the lowest log GSR median value. For the olfactory experiments there is little variance in the median values but the related IQRs have a certain amount of variance. In the final computer task based experiments the log GSR median is raised along with the IQR for the second experiment (E06-PB).

The HR median was down for E01-PB which was the metal puzzle task. For E02-PA on negative recall the HR median was raised and then down for the positive recall E02-PB. For imagery experiments the HR IQR was greater for Disgust and Sadness images. Medians were similar across the five image experiments with the exception of E03-PC which had a lower median for the Fear images.

For the olfactory experiments the HR median were similar for the positive smells of baby powder (E04-PA) and lavender and patchouli (E04-PE). HR median values fell for both the muscle strain cream (E04-PB) and also for the drain cleaner (E04-PD) negative smells. Interestingly the HR median raised up again after the negative smell E04-PB when the coconut smell experiment took place (E04-PC). The HR median fell again for the negative smell E04-PD. For the final experiment group E06, the HR median is the polar opposite of the log GSR median values. It is raised for the first task on the Stroop test while it is then down for the speed reaction test.

For E01 the IBI IQRs vary for the last two experiments. Also the median is higher for the mouse trap experiment than the other three experiments in the group. The IBI shows the opposite effect to that of the HR for E02. Here the IBI is down for E02-PA. The IQRs are different across E03 but the medians are all quite similar. For E04 the medians are very similar for the positive smells E04-PA, E04-PC and E04-PE. The IBI for the expected negative smells are interesting. The IBI median is the lowest of all five for the muscle strain cream (E04-PB), while the IBI median for the drain cleaner (E04-PD) is actually the highest of all five smell experiments. Medians for E06 are similar for both experiments. The only noticeable observation here is that the first quartile for E06-PA is lower than that of E06-PB.

The temperature box plots across all nineteen experiments certainly provide some interesting insights. The skin temperature medians are clearly rising across the four object manipulation experiments for E01. The IQRs are also spread. There are significant median difference between E01-PA (31.77) and E01-PB (32.50), while the Vaseline tin and the mouse trap have similar medians. For E02 recall experiments. The negative recall experiment (E02-PA) shows a reduction in the skin temperature median along with a smaller IQR than the other two experiments in the group.

In relation to the imagery experiments, one significant observation is that for the cat video (E03-PA) and the disgust images (E03-PB), the medians for both are almost identical. This is also the case for these two experiments in relation to the box plots produced for the other sensors. The temperature median significantly reduced for the fear images (E03-PC). The median increased again for the sadness images (E03-PD) and for the final images of relaxation and contentment (E03-PE).

For E04 olfactory experiments, the medians were similar for the first two experiments. They were reduced for the third experiment coconut smell (E04-

PC) and the drain cleaner smell (E04-PD). The median recovered again across the sample population for the final positive lavender and patchouli experiment (E04-PE). In the final two experiments in group E06 the median for the Stroop test was lower than the median for the speed reaction test. Their IQRs were quite similar.

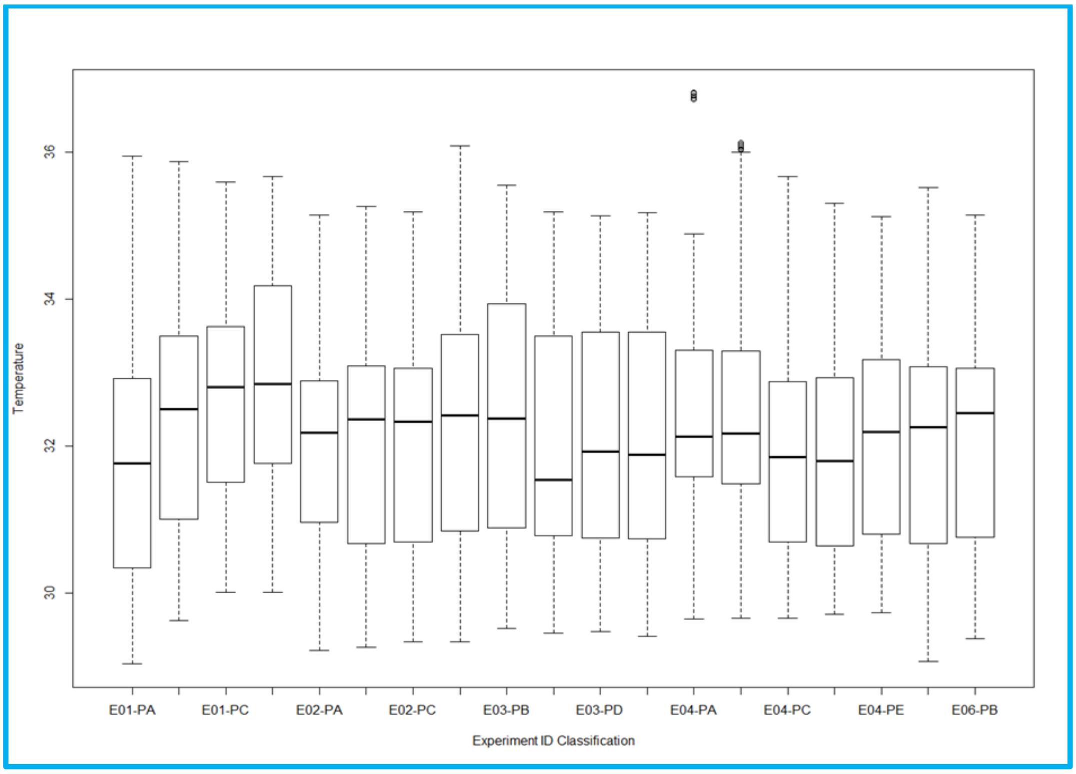



**Figure 5-20 Experiment ID by Temperature**

The Figure 5-20 Experiment ID by Temperature is one of five box plots produced for the experiment ID classification of the E4 sensor values. The Temperature box plots figure has been selected again as it clearly shows variance across all of the nineteen experiments. Skin temperature values in the above box plot can be seen to primarily change across the E01, E03 and E04 groups of experiments. The other experiment ID classification box plots are available in the statistical appendices documents of this thesis in volume 2 of 2.

**Participant IDs (ID) by sensor, reporting and analysis:** Using reported GSR data the majority of participants appear to have very low GSR responses. Participant 2 and 33 have extreme responses while participants 6, 9, 12, 17 and 24 are reasonably responsive to GSR. The log GSR in Figure 5-21 Participant ID by Log GSR presents an extremely different picture. Using the -4 to +2 log GSR scale it is clear that there are significant GSR responses for all 33 participants. The IQR are quite spread for the majority of participants and the median values are all highly variable for each participant. On visual inspection, all 33 participants appear to have different median log GSR values. Two participants, number 8 and 19 have excessive outliers but all others appear to be within reason. Also participant 2 and 33 have extreme responses under their log GSR box plot.

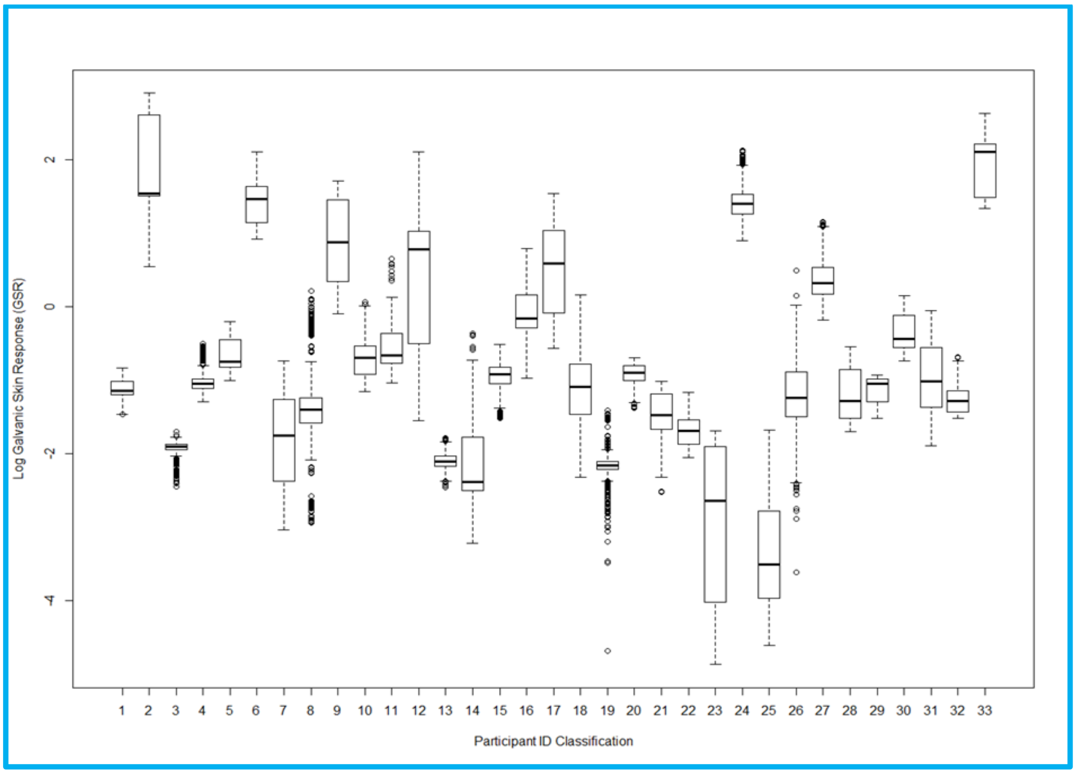



**Figure 5-21 Participant ID by Log GSR**

Similar to the log GSR, there is considerable variance across all 33 participants for the HR data as demonstrated in Figure 5-22 Participant ID by HR. Outliers at the higher quartile end appear to be associated with all participant IDs in the box plot. IQR and median values are also varying considerably and again the majority of values here are quite different across the sample population. The IBI also shows variance across all the sample population. Participants 3, 12, 29 and 31 on the IBI box plots all have raised IBI values. These same four participants were identified in the HR box plot with lower than normal HR data values. For the IBI box plot, the majority of outliers are appearing below the first quartile.

The temperature box plot also demonstrates considerable variance across statistical data and shows up and down trends similar to its histogram when analysed across the sample population. A few participants such as 1, 10, 11 and 19 have a number of excessive outliers in their respective box plots. Participants 4, 8, 9, 14, 18, 24, 26, and 29 have IQR ranges that are quite different for all other participants in the sample population.

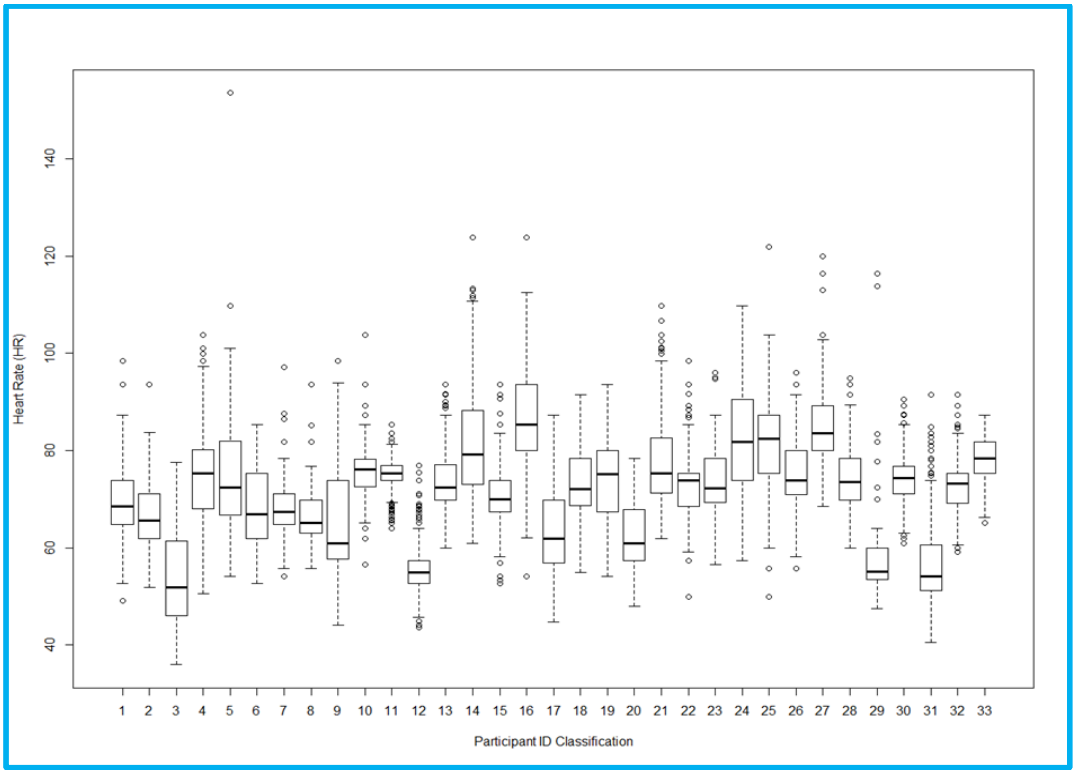



**Figure 5-22 Participant ID by HR**

The two box plot figures above demonstrate participant ID variance across the Log GSR and the HR sensor data stream values.

The other participant ID classification box plots are available in the statistical appendices documents of this thesis in volume 2 of 2. In relation to all of the box plots discussed above there is also a set of macro tables with detailed statistical results across the Emotion, ExpGroup, ExpID, and the participant ID classifications. These tables are provided as reference figures in the statistical appendices section in volume 2 of 2.

### 5.4.4 Macro Vision and Geneva Emotion Wheel (GEW) Analysis

This section presents a different viewpoint and revisits the vision based emotion classification and presents a macro level investigation into the EmotionViewer classification results in conjunction with the GEW self-reporting dataset results.

Each experiment group is reported and analysed at a macro level using both the EmotionViewer classifications and the self-report GEW based emotion classifications. The section also provides further practical insights into the experiment groups both at the vision sensor level and also at the personal self-reporting level. The self-reporting analytical sections present the overall representation of the emotions felt by the thirty three participants in the sample population under the experiment group (ExpGroup) and also at the experiment ID (ExpID) classifications.

**Experiments group E01 dexterity based object interactions:** This section presents results and analysis from the dexterity based group of experiments that involved participants conducting four experimental tasks involving object interactions under time pressure.

**E01 EmotionViewer reporting and analysis:** The Figure 5-23 Experiment Group E01 EmotionViewer Classifications presents a view of all four individual experiments for E01 along with an overall (All) view. The figure represents the camera based emotions picked up by the EmotionViewer adaptor of the EFS.

The relative frequency distribution plot shows a rise in Anger, Contempt and Disgust for the first two experiments (box and metal puzzle) but these values then drop back for the Vaseline (E01-PC) and the mouse trap (E01-PD) experiments. Certainly the first two tasks were challenging considering the time pressure to get the task completed. The Vaseline tin (E01-PC) was messy and annoying but most participants completed this rather quickly.

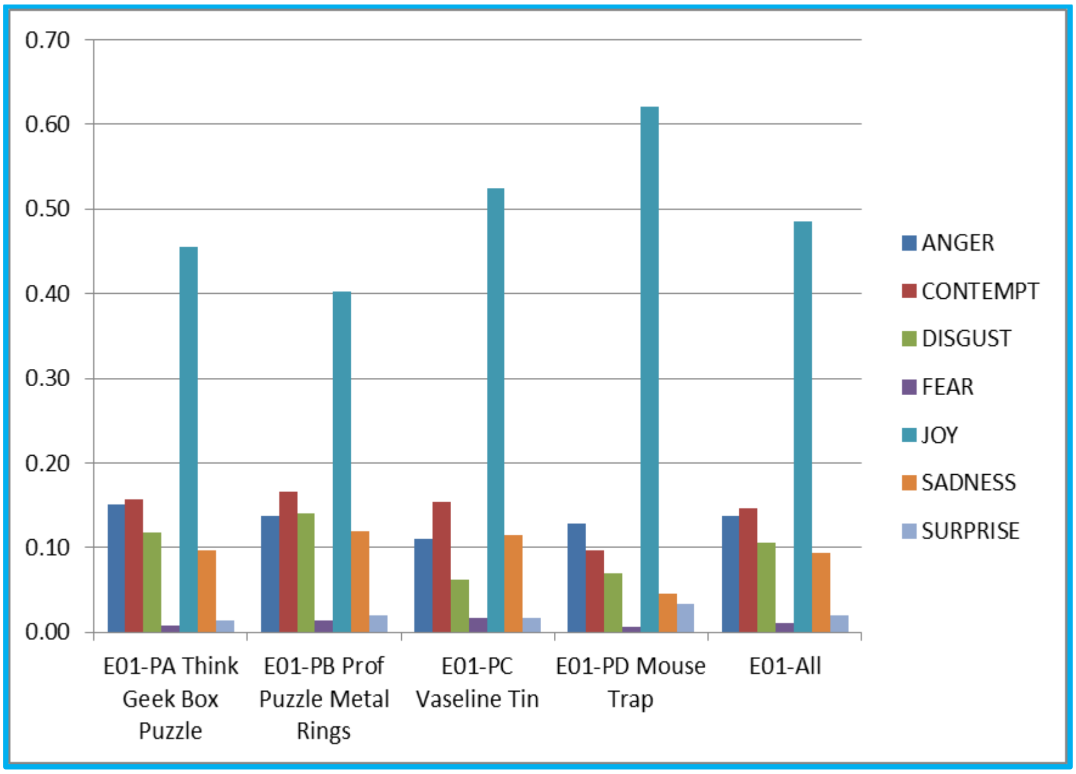



**Figure 5-23 Experiment Group E01 EmotionViewer Classifications**

Generally speaking the mouse trap was well received and participants were pleased when they set-up the trap and also when they were asked to test its activation. The relative increase of Joy throughout is generally consistent with how participants felt while they worked through the four dexterity tasks. In summary the vision sensor picked up a balanced mixture of positive and negative emotions for the four dexterity experiments.

**E01 GEW reporting and analysis:** From the Figure 5-24 Experiment Group E01 GEW Self-Reporting Classifications, all the experiments provided strong values of Interest, Amusement and Joy. For the box puzzle, Anger stands out as the dominant negative emotion also with smaller values of Fear and Hate. Relief is also picked up for the box puzzle which possibly relates to having opened the box.

The metal puzzle is quite close in emotion classification to the box puzzle and also has similar positive emotion reported. It also reports Anger, Hate and Contempt. Most interesting is Disappointment which may be due to the fact that very few participants were able to solve the metal rings puzzle within the allocated time period.

The Vaseline tin was a very quick experiment for most participants and almost all were able to open the tin which was purposely made slippery on the outside. Again the positive emotions are comparable to the other experiments. Relief is prominent and possibly relates to having completed a rather messy disgusting task. Anger and Hate do not appear so strongly in the self-reporting data but significantly Disgust is the most dominant negative emotion felt and reported by participants. This emotional response is possibly due to the unsightly contents of the Vaseline tin when it was opened. Generally speaking, once it was opened, each participant just wanted to get rid of the tin and to get their hands cleaned up.

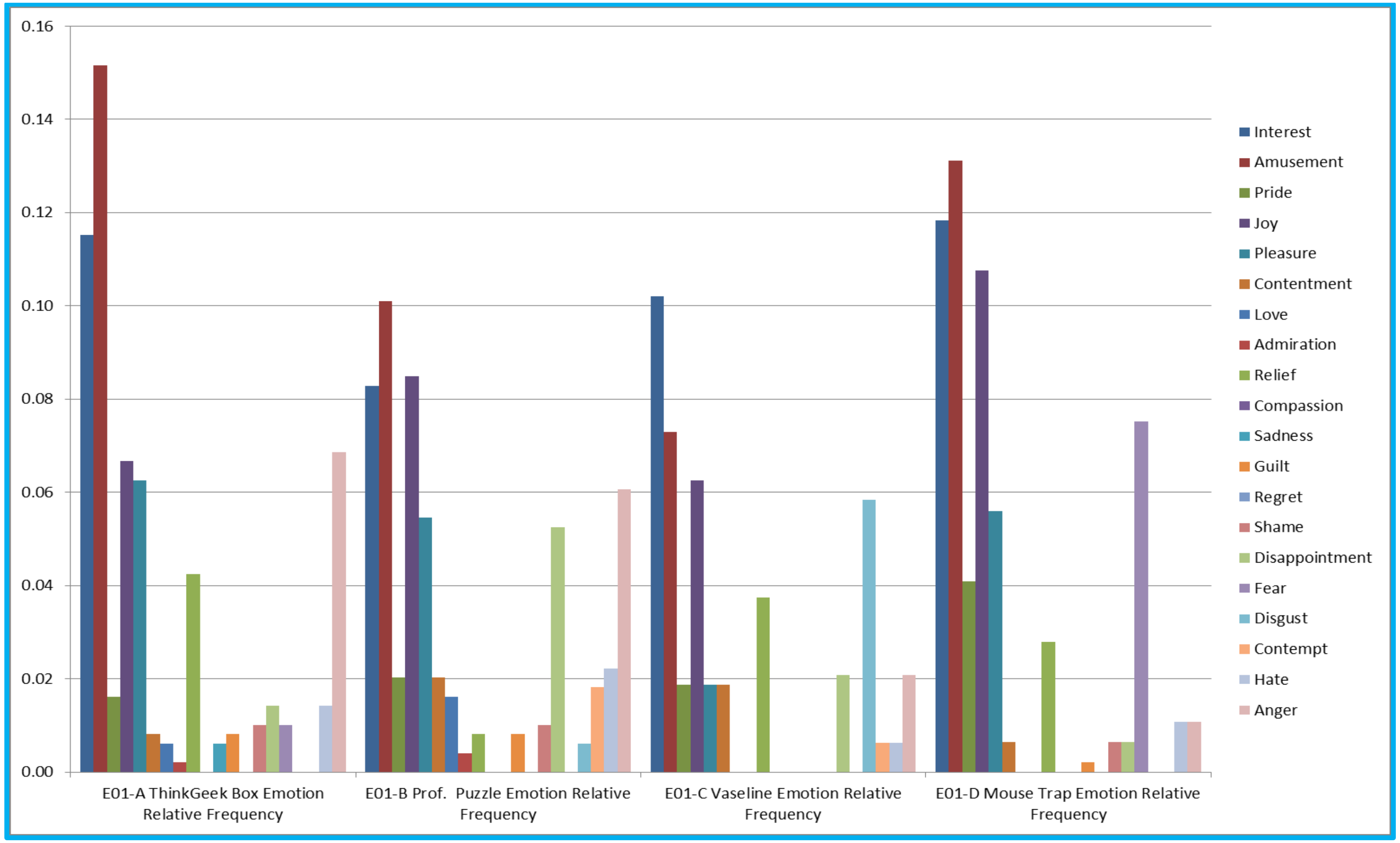



**Figure 5-24 Experiment Group E01 GEW Self-Reporting Classifications**

Finally the mouse trap shows strong positive emotions of Interest, Amusement, Pride, Joy and Pleasure for most participants. Fear is clearly felt as the most dominant negative emotion with minor aspect of Anger and Hate. While the mouse trap was a fun experiment positioned as the last task in the object dexterity/interaction group, the majority of participants enjoyed the task. Their strong reported feelings of Fear are certainly attributed to the fact they may hurt their fingers in the process of setting the mouse trap.

The bar plot Figure 5-25 Experiment Group E01 GEW Self-Reporting Overall presents the total intensity scores and the relative frequencies across all of the four dexterity experiments in group E01. The overall self-report summary for this group is that positive emotions were primarily reported throughout all four tasks. While negative emotions do not compare with the positive emotions in terms of score values their presence are consistent and relate directly to the type of emotional experience that was aimed at for the specific experimental task. If participants were given longer on certain tasks, or if the experiment tasks were perhaps made more difficult to complete, then there may be marked increases in the negative emotion values across the group of experiments.

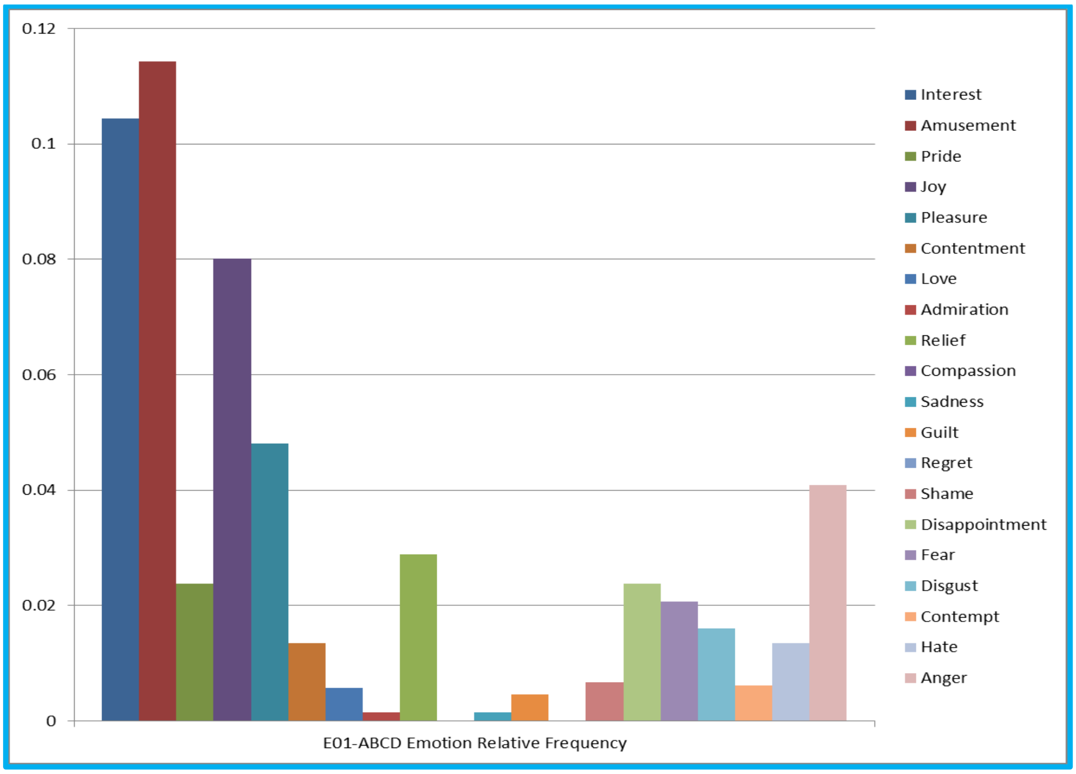



**Figure 5-25 Experiment Group E01 GEW Self-Reporting Overall**

From both the EmotionViewer and the GEW self-reporting plots produced above the balance of positive and negative emotions across E01 are demonstrated above as being relatively correlated across the four experiments.

**Experiments group E02 cognitive based:** This section presents results and analysis from the cognitive recall group of experiments. Participants conducted three experiments involving thought processes to cognitively recall negative and positive emotional experiences either past, present or future. One factor to be cognizant of in relation to this experiment is that it was primarily a silent experiment with the participant in front of the camera silently recalling the emotional experience.

**E02 EmotionViewer reporting and analysis:** Based on the Figure 5-26 Experiment Group E02 EmotionViewer Classifications the vision sensor data picked up stronger negative emotions (Anger, Disgust and Sadness) for the first negative recall experiment.

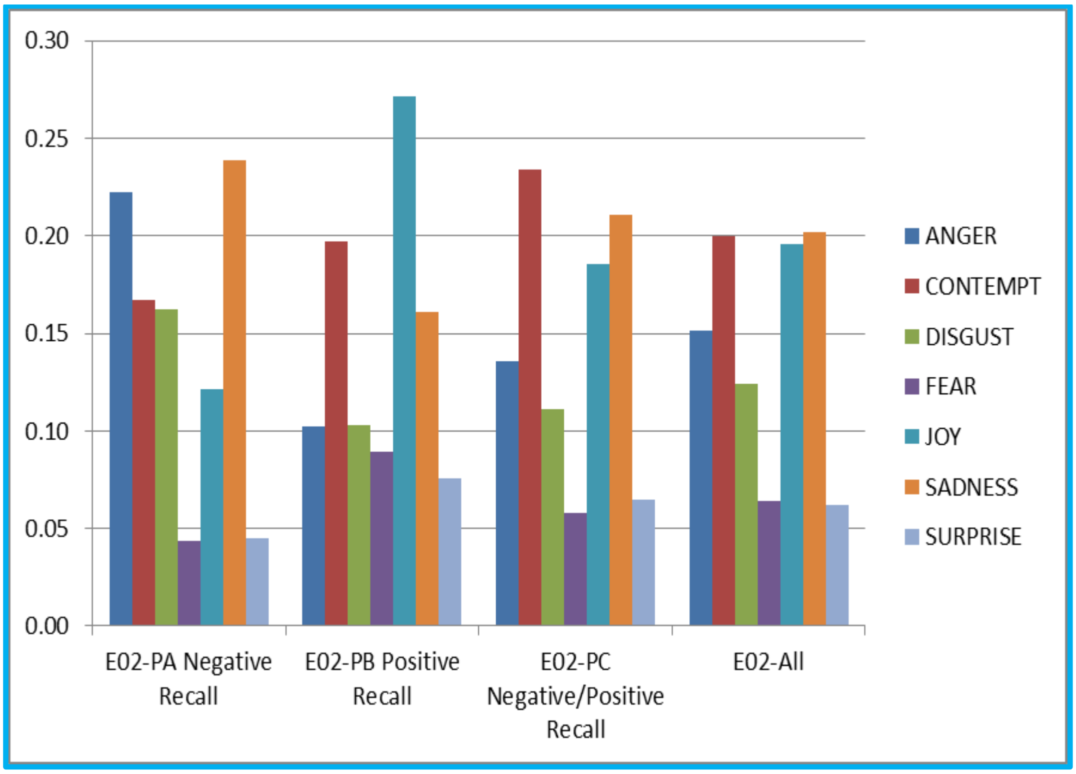



**Figure 5-26 Experiment Group E02 EmotionViewer Classifications**

Joy is the most dominant emotion picked up for the second positive emotional recall experiment but strong negative emotions have also been picked up such as Sadness and Contempt along with others. The final experiment of mixed emotional recall has a mixture of emotions classified but there is a clear drop in positive Joy from a relative frequency of 0.27 to 0.19.

Overall the vision sensor primarily picked up negative emotions and the lack of facial expressions when a person is typically discussing an emotional experience is clearly a limiting factor. The above plot shows a trend of negative to positive emotions for the first two experiments. In relation to the last experiment, the plot shows a mixture of emotions with a certain element of Joy also classified.

One other finding relevant to this group of experiments is that Contempt can be classified when facial expression is quite neutral, neither positive nor negative in expression. Contempt and Sadness values are quite strong throughout all three experiments and may well be applicable to the lack of real facial expression in participants as they just faced the camera during the cognitive recall experiments.

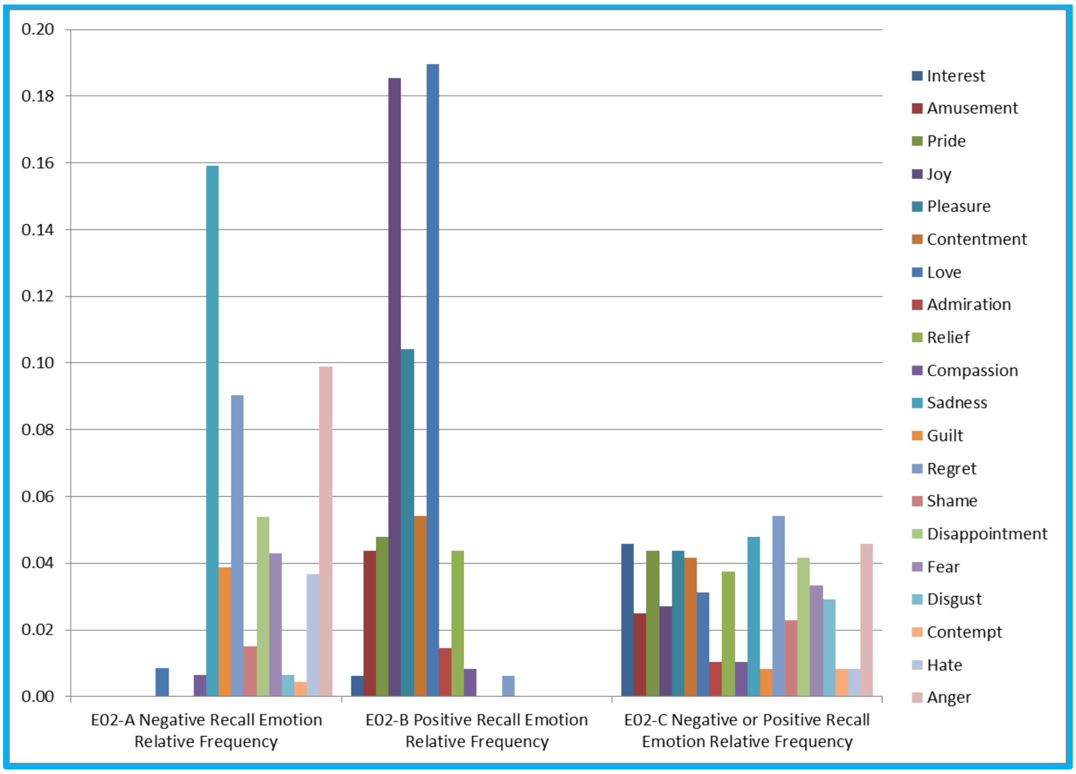



**Figure 5-27 Experiment Group E02 GEW Self-Reporting Classifications**

**E02 GEW reporting and analysis:** The Figure 5-27 Experiment Group E02 GEW Self-Reporting Classifications directly reflect the flow of the cognitive recall experiment. Negative emotions are clearly most dominant for the first experiments. Sadness, Regret and Anger are clearly the strongest emotions that were felt. The second positive recall is also as expected and participants reported Joy, Love and Pleasure as the most dominant positive emotions felt throughout the experiment.

As the final recall was open to participant choice of positive or negative, there is a clear mixture of emotions from the participant self-report data. Sadness, Regret, Disappointment and Anger stand out from a broad span of emotions on the negative side while Pride, Pleasure and Contentment are the strongest for positive emotional feelings.

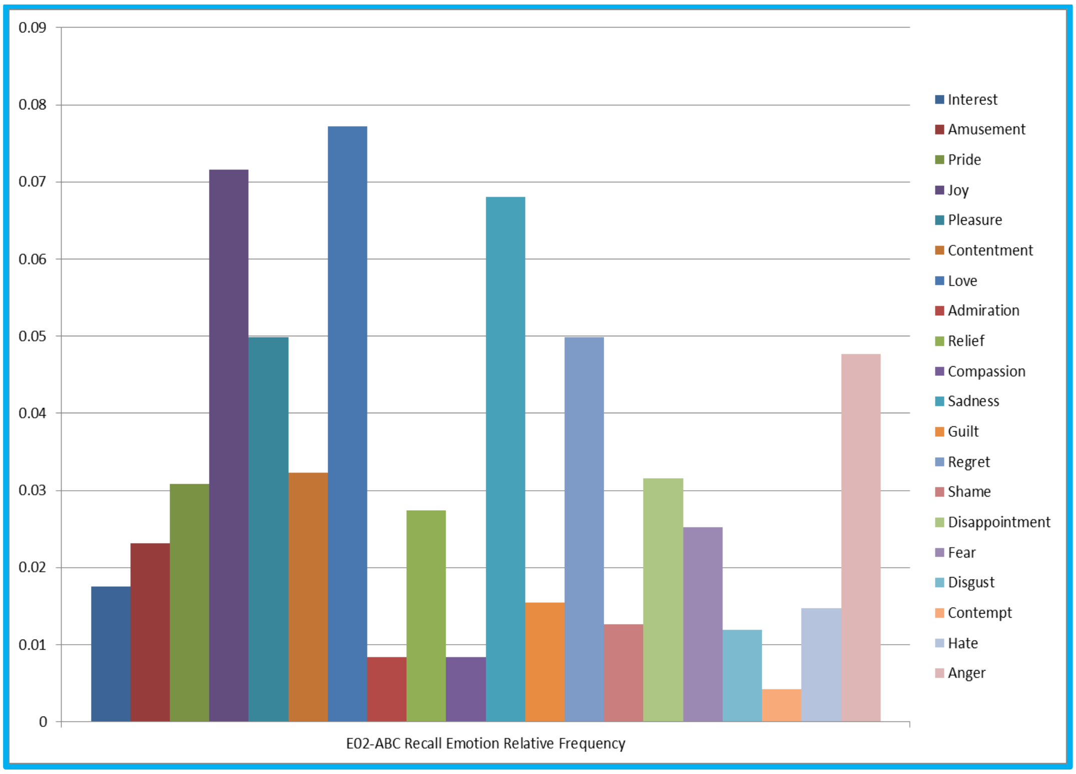



**Figure 5-28 Experiment Group E02 Self-Reporting Overall**

From the Figure 5-28 Experiment Group E02 Self-Reporting Overall the feelings of Love, Joy and Pleasure are the most dominant positive emotions felt. Sadness, Regret and Anger are the most dominant negative emotions felt throughout the three experiments. Other emotions deserving comment are Relief which is possibly due to the cognitive strain of this experiment which was difficult for participants. Pride also appeared which possibly relates to positive recall relating to academic, life or sport related achievements. Guilt and Fear are also interesting negative emotions felt by participants.

For both the EmotionViewer and the self-reporting data presented in the above plots, negative emotions are evident for the first experiment, positive emotions are more evident for the second experiment and the third experiment is a clear mixture of positive and negative emotions.

**Experiments group E03 visual based:** This section presents results and analysis from the imagery group of experiments that required participants to conduct five experiments involving the viewing of images aimed at the stimulation of emotions in participants. The first experiment E03-PA involved the participants viewing a short video of a cat that put its head into a tissue box. Experiments E03-PB to E03-PE involved a series of images around the emotional themes of Disgust (E03-PB), Fear (E03-PC), Sadness (E03-PD) and Relaxed/Content (E03-PE) respectfully. The video ran for 90+ seconds while the images ran for approximately one minute for each of the emotional themes.

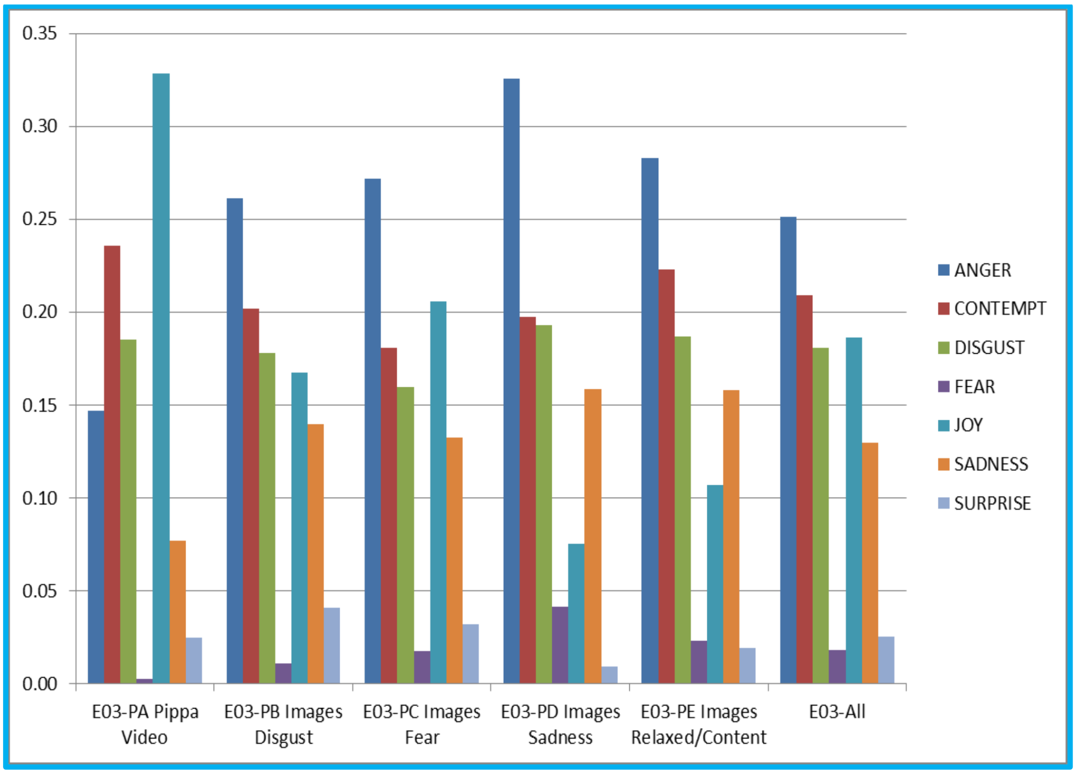



**Figure 5-29 Experiment Group E03 EmotionViewer Classifications**

**E03 EmotionViewer reporting and analysis:** Classification results from E03 are provided in Figure 5-29 Experiment Group E03 EmotionViewer Classifications. The first experiment used the cat (Pippa) video with the vision sensor picking up a range of mixed emotions with high values for Contempt, Disgust and also Anger. This was contrasted with a very strong percentage of

Joy emotion expressions. Overall negative emotions were the strongest based on the vision sensor classification.

The second experiment presented a number of images around the emotional theme of Disgust. Anger and Contempt were strongest here but there was an 18% classification of Disgust. When combined with Anger this rises to 48% across the Disgust image theme. Sadness was also picked up and is also relevant considering some of the images that were presented. The classification of Joy is also identified and may be due to participants smiling at an image or a slight Disgust expression being interpreted as a Joy expression. Overall the negative emotions classified were the most dominant for experiment E03-PB.

The images for E03-PC did not generate any major classification of Fear. Anger, Contempt and Disgust were quite dominant as per the previous experiment. Joy and Sadness were also strong emotions classified and perhaps reflect some of the attitudes displayed by participants (thought they were funny) while watching the Fear images. E03-PD shows a clear reduction in Joy and a justified increase in Sadness expression and a major jump in Anger emotion expressions. This is representative of the imagery that showed sad situations/events that may have made participants feel angry as to why they had occurred in the first place.

The final experiment E03-PE showed relaxed and contented images such as a desert island, hammocks, setting sun, etc. Clearly this did not create a major increase in Joy for participants. The negative emotion expressions classified could be due to the lack of facial expressions while watching the final images and also perhaps tiredness may have been a factor here.

Overall scores for this group of experiments clearly identify negative emotions as being the most dominant across the sample population. The cat video while expected to generate Joy, upset a lot of participants who did not see the funny side and were quite upset emotionally at the content. The three experiments E03-PB, E03-PC and E03-PD are all negatively related emotions and thus justify the negative emotional swing across the group of experiments. In summation, when the imagery group of experiments is viewed as a whole, the overall vision sensor emotion recognition results appear to quite closely reflect the typical expected outcomes.

**E03 GEW reporting and analysis:** With reference to Figure 5-30 Experiment Group E03 GEW Self-Reporting Classifications for the first experiment, using the cat video, Amusement, Joy and Pleasure were strongly reported with Amusement having the highest relative frequency. There were also strong negative emotions felt with Anger having the second highest value. Significantly Disgust and Compassion were also felt strongly according to the self-report data.

Primarily the second experiment produced Disgust as the highest emotion felt after watching the images. Participants also felt feelings of Sadness, Disappointment, Contempt, Hate and Anger. The third experiment produced a mixture of Amusement and Fear which is interesting considering the imagery was related to Fear. Participants also felt Contempt, Hate and Anger.

The fourth experiment clearly produced Sadness in participants after viewing the images. Compassion was also strong in the self-report data. Guilt, Shame and Anger are also other negative emotions felt during this experiment. The final experiment showing images of relaxation and contentment produced high self-report data for feelings of Contentment, Joy, Pleasure and Relief. Minimum negative emotional feelings were reported.

The totals across all the E03 experiments shown in Figure 5-31 Experiment Group E03 GEW Self-Reporting Overall tend more towards a dominance of negative emotions from the five imagery based experiments. For negative emotions felt overall, Sadness, Disgust, and Anger are the highest relative frequencies. Compassion could also perhaps be aligned with Sadness. On the positive emotion side, there was strong evidence of Amusement, Joy, Contentment and Pleasure being felt by participants as they watched and thought about the various images.

Overall the self-reporting plots are closely matched with the EmotionViewer for all of the E03 experiments with the exception of E03-PE. The EmotionViewer picked up negative emotions for E03-PE, generally not attributed to the type of experiment which involved relaxing images.

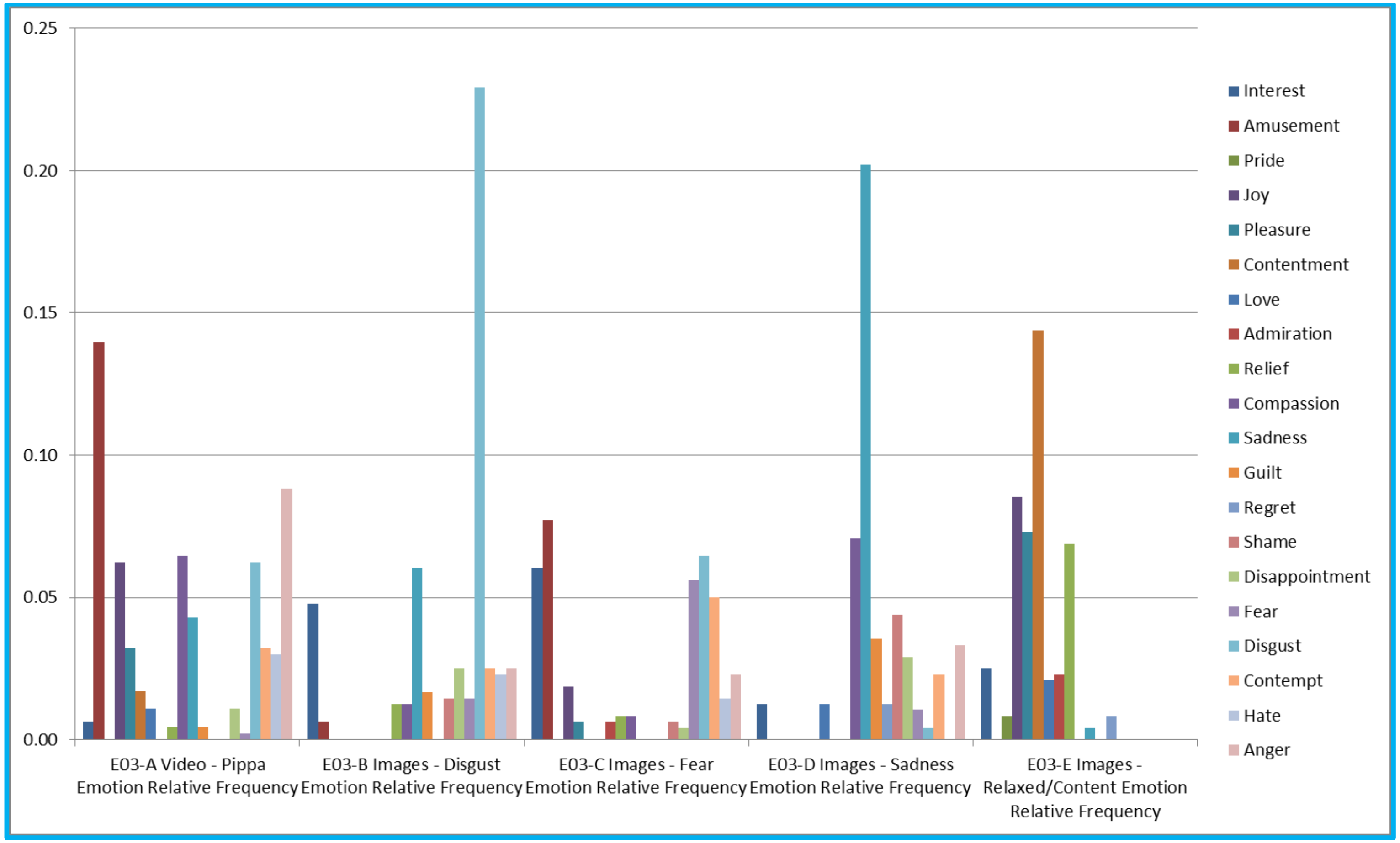



**Figure 5-30 Experiment Group E03 GEW Self-Reporting Classifications**

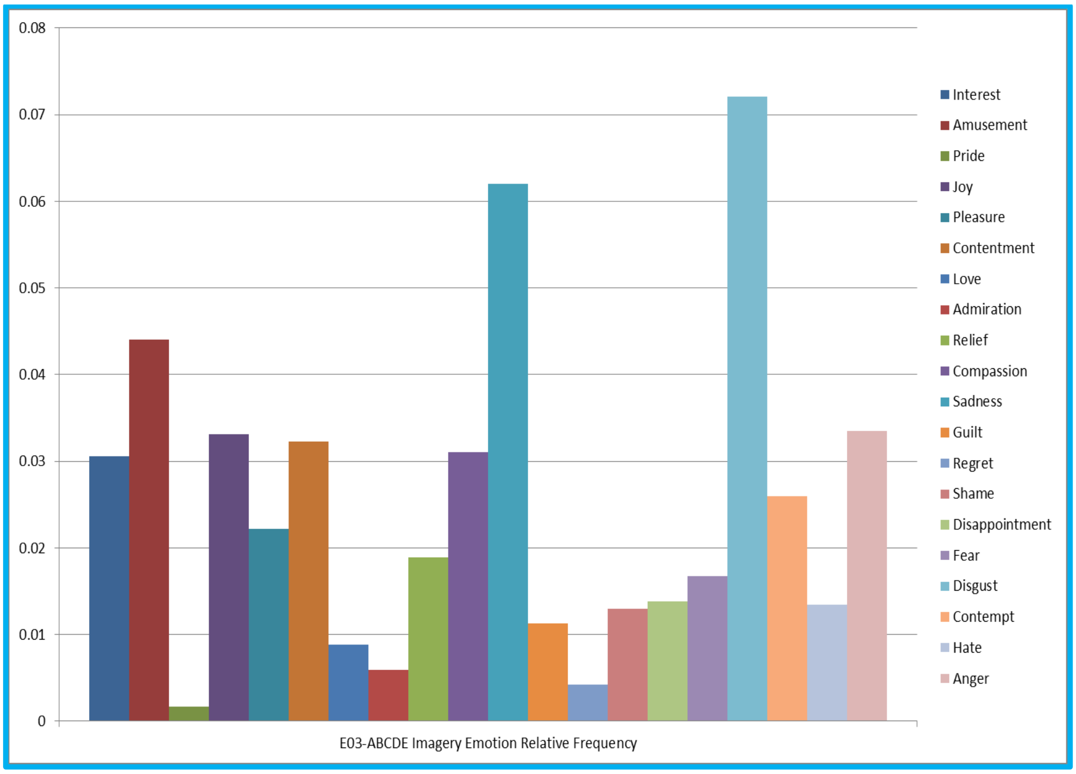



**Figure 5-31 Experiment Group E03 GEW Self-Reporting Overall**

**Experiments group E04 olfactory based:** This section presents results from the emotion classification performed by the vision sensor from the EFS software and the GEW self-report data. The analysis and bar plots below represent the computed total from all participants for each of the five experiments in the E04 olfactory group of experiments.

For clarification purposes, the first experiment E04-PA involved the participants smelling baby powder. E04-PB was the smell of muscle strain cream (Deep Heat), E04-PC used the smell of coconut and E04-PD used the smell of drain cleaner (Jeyes Fluid). The final smell E04-PE used a mixture of lavender and patchouli. This was a very intense set of experiments and generally each experiment involved opening a vessel, smelling the substance for between 15 to 25 seconds which included thinking about the smell and then completing the GEW self-report form after the experiment itself. This was carried out for all five smell experiments in the olfactory group.

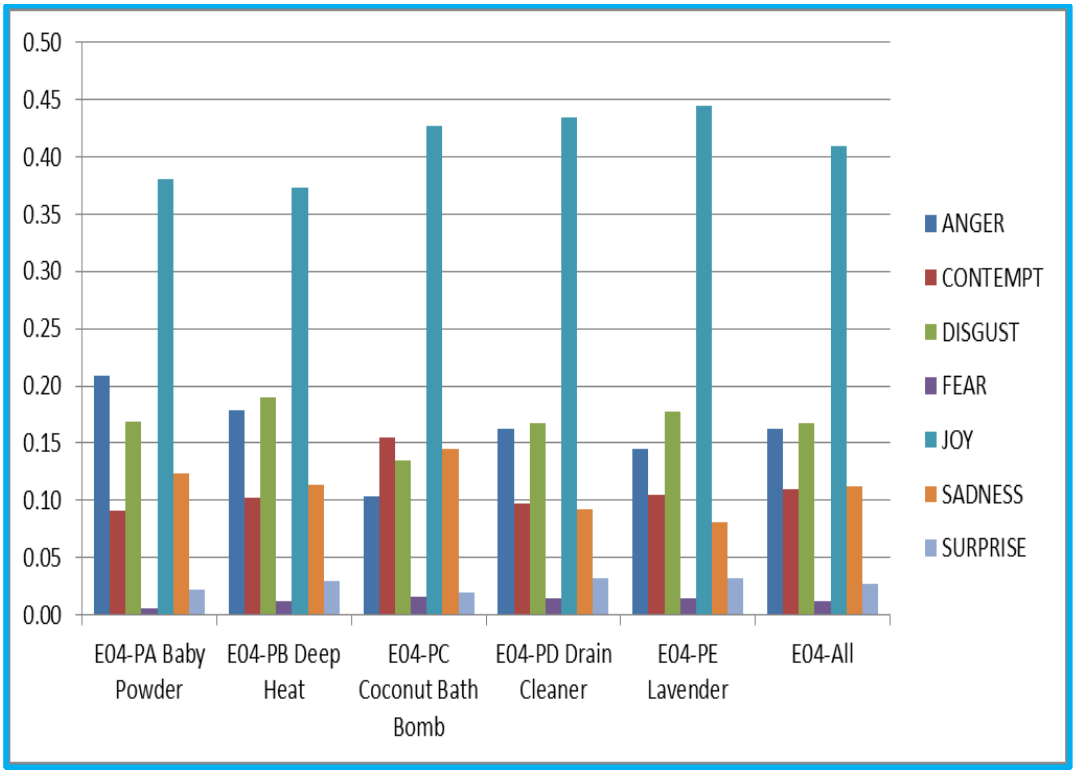



**Figure 5-32 Experiment Group E04 EmotionViewer Classifications**

**E04 EmotionViewer reporting and analysis:** Classification results from E04 are provided in Figure 5-32 Experiment Group E04 EmotionViewer Classifications. Joy is the most dominant emotion classification across all of the olfactory experiments and hits consistent percentages of 35% plus across all five experiments. Joy was an expected emotion in relation to the first (baby powder), third (coconut), and the last (lavender and patchouli) experiments and is reflected in the EmotionViewer data. All of the E04 experiments record percentages of Disgust, Anger and Sadness (to a lesser extent), which when combined present a significant presence of negative emotions. Interestingly the Disgust and Anger classification percentages were at their lowest for the third experiment involving the coconut bath bomb while Sadness was at its highest percentage.

**E04 GEW reporting and analysis:** With reference to the Figure 5-33 Experiment Group E04 GEW Self-Reporting Classifications, the first experiment in the olfactory group used a typical smell related with baby powder. The smell dominantly produced feelings of Pleasure, Love and Joy. Other feelings of Contentment and Relief were also felt by participants.

The second experiment used the sports related deep heat muscle strain cream. Strangely, Pleasure was the most dominant emotion felt in relation to this smell. Relief was also listed along with Joy and Contentment. There was not such a negative response to this smell but participants did feel Disgust, Contempt and also feelings of Hate during this experiment. The third olfactory experiment used a coconut type smell and the self-report data was mostly positive emotions. Again Pleasure, Love, Joy and Contentment were strongly felt by the participants with the highest relative frequencies reported.

The fourth experiment used a smell from a drain cleaning product. Disgust was the strongest emotion reported and there were also reports of Hate, Contempt and Anger from participants. Strangely this smell also attracted some positive emotional feelings of Joy, Amusement, Pleasure, Contentment and Love. This was interesting and may be a factor that a number of participants got an oil type related smell from the sample provided.

The final smell of lavender and patchouli soap produced positive emotional feeling in participants. Pleasure was the most dominant emotional feeling reported and was followed by strong values for Love, Joy and Contentment. Some participants did not seem to like this smell and reported feelings of Disgust and Hate. It also generated a feeling/memory of Sadness for other participants.

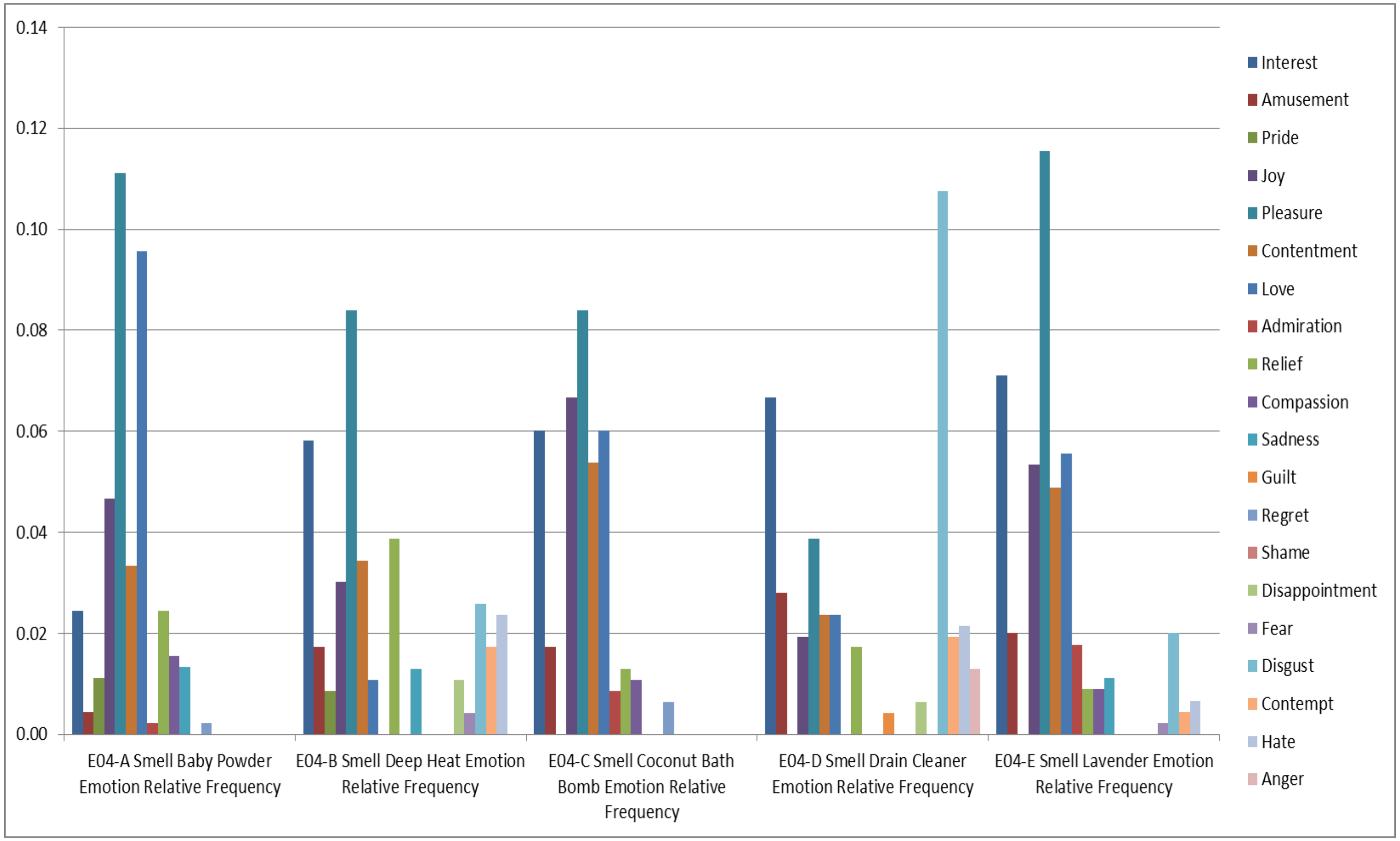



**Figure 5-33 Experiment Group E04 GEW Self-Reporting Classifications**

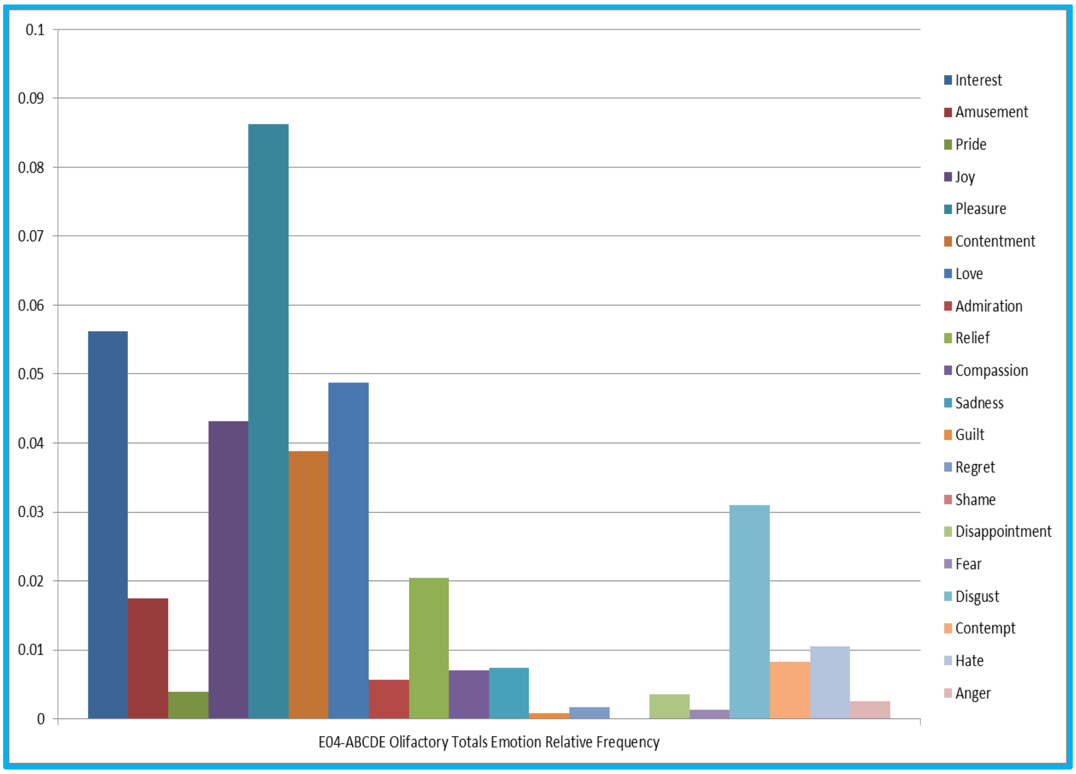



**Figure 5-34 Experiment Group E04 GEW Self-Reporting Overall**

As reported in Figure 5-34 Experiment Group E04 GEW Self-Reporting Overall the olfactory group of experiments predominantly produced positive emotional reporting from participants. Pleasure, Love, Joy and Contentment were strongly felt by participants. Disgust was the most dominant negative emotional feeling. There were also feelings of Hate, Contempt and Anger. The cluster around Relief, Compassion and Sadness are interesting and could possibly relate to cognitive recall memories brought about by the specific smells experienced by participants.

Clearly the self-report data is a closer fit to the types of smells introduced to participants. The EmotionViewer lacks clear differentiation across the various smells. This may have been a factor due to the experiment set-up with loss of vision data while the smell experiments were being manipulated by the participants.

**Experiments group E06 gaming based:** This section presents results and analysis from the computer stress based E06 group of experiments that involved participants conducting two experimental tasks involving the Stroop psychological based game and also a colour based reflex speed test aimed at the stimulation of emotions in participants.

For clarification purposes the first experiment E06-PA involved the participants playing a computer game based on the Stroop test. This game had five levels the participant had to complete. Once they had completed all five levels of the game they had to record their score and then aim to beat their score by playing the game again with all five levels. For most participants the Stroop test game was completed in between three to five minutes.

The second experiment E06-PB was a speed reaction test. Participants were presented with a browser and there was a small box in which they had to click their mouse once the colour in the box changed. Participants had to do this test for approximately two minutes with the aim to get as close to the ultimate speed of 0.2 of a second.

**E06 EmotionViewer reporting and analysis:** Classification results from E06 are provided in Figure 5-35 Experiment Group E06 EmotionViewer Classifications. The first experiment produced mainly negative emotions with Anger at 28%, Disgust at 17% and Sadness at 17%. Joy was picked up at 16% and is very low if the three main negative emotions of Anger, Disgust and Sadness (total of 62%) are considered as a whole. This experiment was negatively received according to the vision classification data. The speed reaction text was also strong on Anger at 26%, Disgust at 12% and Sadness at

15%. Joy was up as 29%. Overall, negative emotions were picked up in the EmotionViewer facial vision data.

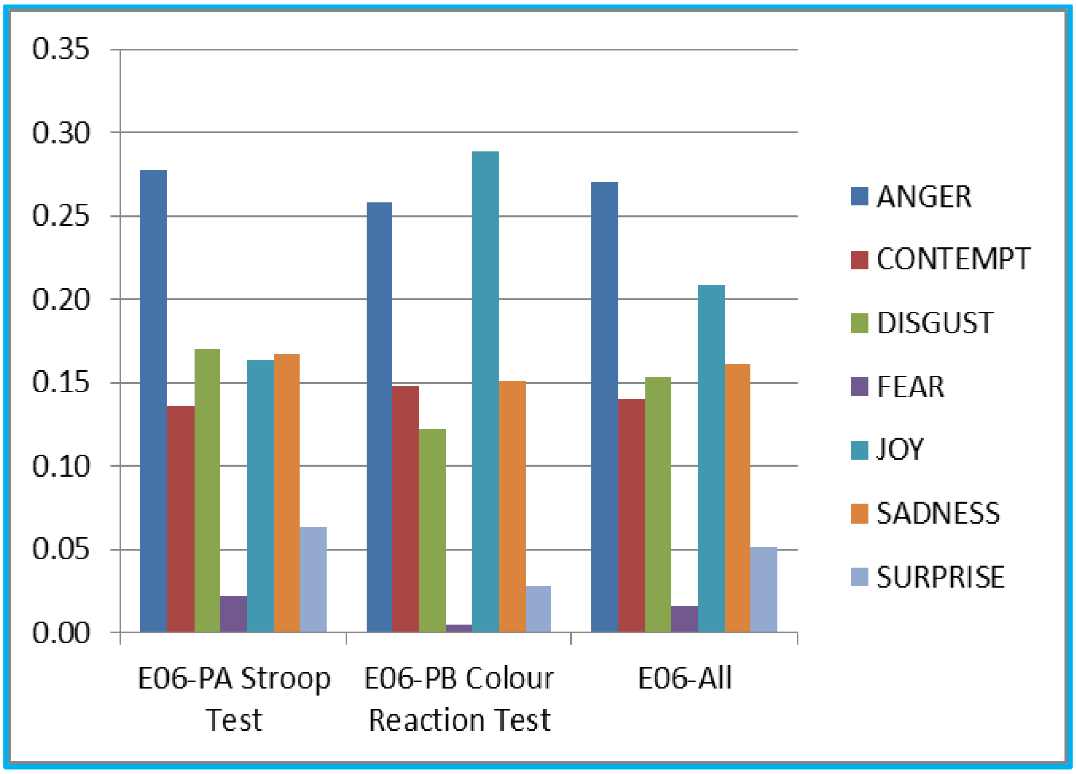



**Figure 5-35 Experiment Group E06 EmotionViewer Classifications**

**E06 GEW reporting and analysis:** The GEW results for E06 are provided in Figure 5-36 Experiment Group E06 GEW Self-Reporting Classifications. The Stroop test created high feelings of Anger in participants along with Disappointment, Shame and Hate. They also felt positive emotions with strong feelings of Amusement, Pleasure and Joy. Relief was also a dominant emotion felt and is possibly related to having completed the computer stress task within a reasonable time frame. There was also the emotion of Pride in the data which again is a relevant feeling having completed the Stroop test.

The second reflex reaction experiment also had negative emotions but they were not as strongly felt as the previous Stroop test. For the reaction experiment, Anger and Disappointment were both significantly recorded by participants. There were also feelings of Shame, Hate, Guilt and Regret in the data. Notably, Relief had a substantial drop for this experiment. Participants again felt the positive emotional feelings of Amusement, Pleasure, Joy and also Pride for the reaction experiment. Both experiments also recorded a strong Interest (Attention) level by participants throughout.

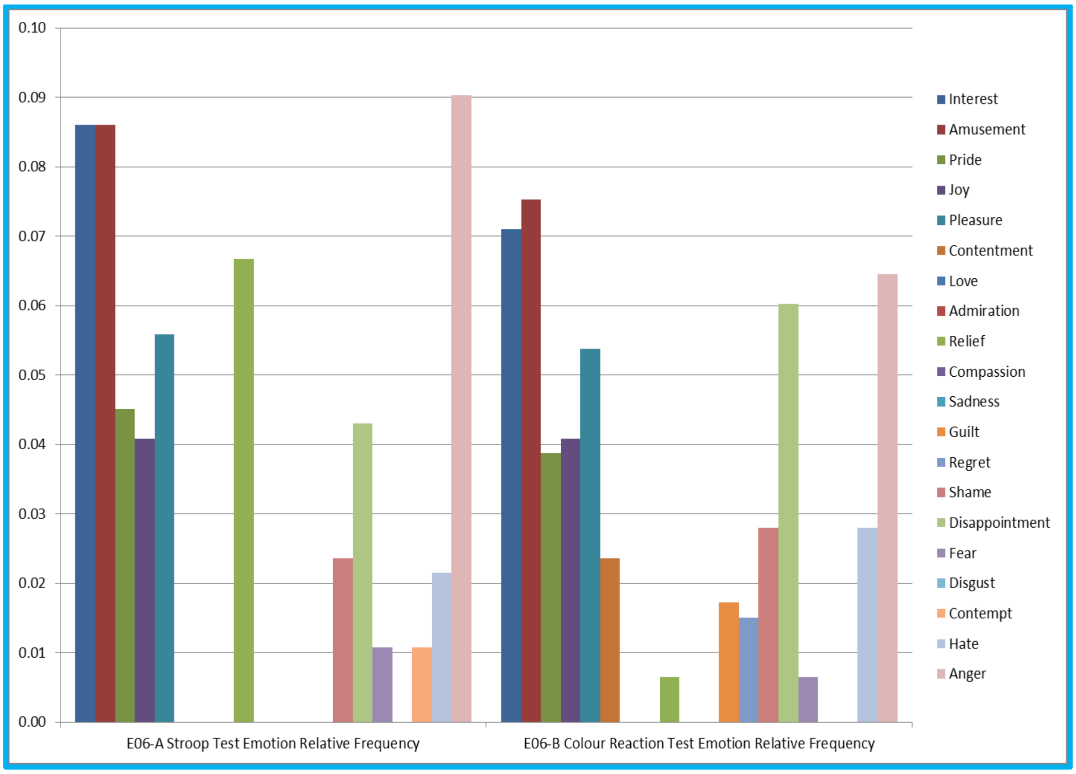



**Figure 5-36 Experiment Group E06 GEW Self-Reporting Classifications**

The combined results shown in Figure 5-37 Experiment Group E06 GEW Self-Reporting Overall from the computer stress based tasks show that Anger and Disappointment were the most dominant negative emotions felt, followed by Shame and Hate. Relief almost acts as a divider between the positive and negative feelings expressed by participants. On the positive spectrum, Amusement and Pleasure were most dominant along with levels of Pride and Joy being felt by participants.

Overall the self-report data demonstrates a mixed set of emotions. Participants seem to have enjoyed the tasks but they also made then Angry and perhaps stressed along with feelings of negativity in terms of their achievement/capabilities (Disappointment) across both experiments. This summary is also somewhat reflected in the EmotionViewer data where primarily negative emotions dominate but a strong degree of the Joy emotion was also classified from the vision frame data.

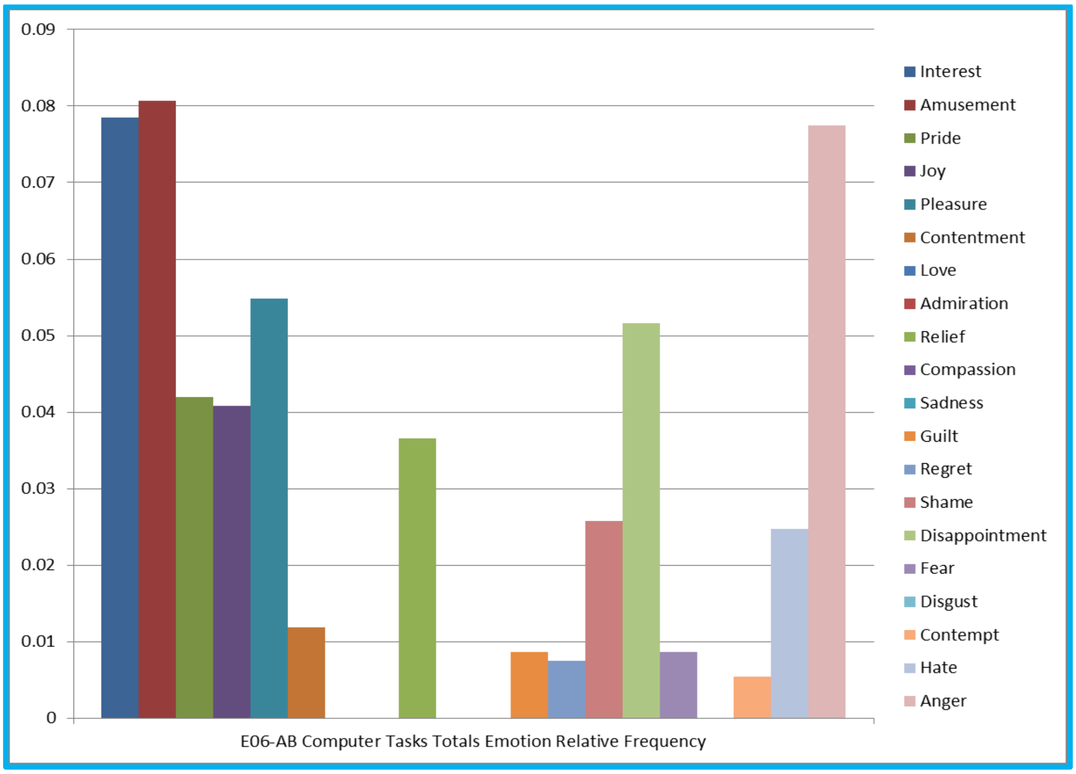



**Figure 5-37 Experiment Group E06 GEW Self-Reporting Overall**

This chapter section has presented macro reporting and analysis across the experiments total master dataset and has discussed high-level findings at the Emotion, ExpGroup, ExpID and the participant (ID) classification levels. It has also reported and analysed these classifications in relation to the E4 sensor data streams for the GSR, Log GSR, HR, IBI and Temperature. The final sub-section presented reporting, analysis, and practical correlation data and discussion on the GEW self-reporting data aligned with the EmotionViewer classifications for each of the experiment groups. The main summary findings and conclusions of the macro reporting and analysis will be provided in the closing section of this chapter.

## 5.5 Micro Statistical Evaluation: Hypothesis Reporting and Analysis

This section presents discussion and analysis of the statistical reporting and results that were produced from all thirty three individual experiment datasets (produced for each participant) at a micro level across the same classification tracks discussed previously at the macro level. The first section presents reporting and analysis across individual sensor statistics and their related histograms. The next section provides summary reporting and analysis across the classifications of emotions (Emotion), experiment groups (ExpGroup) and experiment IDs (ExpID) for the E4 sensor data streams.

The reader is advised to refer to the statistical reporting appendices documents in volume 2 of 2 of the thesis for reference purposes while reading this section.

### 5.5.1 Micro Sensor Statistics and Histograms

Firstly this section presents reporting and analysis with reference to sensor data statistical tables prepared for the four sensor data streams for all thirty three participants using their individual datasets generated from the original total master dataset. This is then followed by reporting and analysis relating to all thirty three individual histograms produced for all participants across the four sensor data streams.

The sensor statistical tables are referenced below as extracts only and are provided in various figures. The actual sensor statistics tables are available in the statistical appendices to the thesis in volume 2 of 2.

**Participant GSR sensor data stream statistics:** The mean value for GSR ranged from 0.05 to 8.16. Eight of the participants had a mean GSR rate over 1.0. The mean GSR jumped to 8.16 for participant number two who also has the maximum GSR value for the sample. The SD values ranged from 0.01 to 5.21

across the sample group of thirty three participants. SD values were also over 1.0 for seven out of eight of the participants with GSR over 1.0.

**Participant HR sensor data stream statistics:** Across the sample population, the mean HR spread was from 52.88 to 84.72. This shows significant variance in the mean HR across the sample group. The SD for participants was also varied. This ranged from 3.45 to 24.34. The SD value of 24.34 can be attributed to the maximum HR for participant five which was recorded as 153.59 (verified in the raw sensor data file). Other than participant five's SD value the next highest SD was 13.39 for participant ID 16 which reported a maximum HR of 123.86.

**Participant IBI sensor data stream statistics:** The mean for the IBI ranges from 0.68 to 1.19. There are a relatively smooth set of values across the sample population. Means are similar for individuals but there is a unique value for each one computed. The SD values range from 0.02 to 0.16. The SD increased smoothly across the sample and similar to the mean, no two SD values are equal.

**Participant Temperature sensor data stream statistics:** For skin temperature, the mean values range from 29.74 to 35.11. There are no equal mean values in the sample and also no significant jumps in the mean skin temperature for each individual. The SD for skin temperature ranges from 0.13 to 0.93. Note that while there are no identical SD skin temperature values in the sample, the SD value differences are into fractional changes and require four decimal places at least to identify SD variance across individuals for the skin temperature data stream.

**Sensor histograms:** This section presents histogram related reporting and analysis across each participant's individual dataset generated from the compiled total master dataset. Reporting, observations and analytical discussion is provided on the individual historgrams produced for all 33 participants in the experiments.  No actual histograms are reproduced in this section but are available in the statistical appendices of the thesis documentation in volume 2 of 2.

**Individual Participant GSR Histograms:** Following a visual inspection of the raw GSR histograms the following participants in Figure 5-38 Sensor Statistic Table Extract for GSR have been found to have a strong degree of variance in their recorded GSR sensor data streams.  These are participants 2, 6, 9, 12, 17, 24, 27, and 33.

| GSR Sensor Statistics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ID | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max. | IQR | Variance | SD |
| 2 | 1.7313 | 4.5462 | 4.7013 | 8.1639 | 13.6976 | 18.3659 | 9.1514 | 27.2477 | 5.2199 |
| 6 | 2.5140 | 3.1474 | 4.3247 | 4.3848 | 5.1741 | 8.2401 | 2.0267 | 1.9801 | 1.4071 |
| 9 | 0.9107 | 1.4130 | 2.4041 | 2.9148 | 4.3047 | 5.5390 | 2.8917 | 2.3617 | 1.5368 |
| 12 | 0.2121 | 0.6056 | 2.1829 | 1.9777 | 2.7904 | 8.2459 | 2.1848 | 1.9609 | 1.4003 |
| 17 | 0.5721 | 0.9205 | 1.7993 | 1.9299 | 2.8485 | 4.6732 | 1.9280 | 1.1051 | 1.0512 |
| 24 | 2.4631 | 3.5485 | 4.0813 | 4.3193 | 4.6371 | 8.4072 | 1.0887 | 1.4590 | 1.2079 |
| 27 | 0.8340 | 1.1882 | 1.3859 | 1.5899 | 1.7197 | 3.1867 | 0.5315 | 0.3094 | 0.5562 |
| 33 | 3.8184 | 4.4286 | 8.2365 | 7.5170 | 9.1485 | 13.9649 | 4.7199 | 6.5639 | 2.5620 |

**Figure 5-38 Sensor Statistic Table Extract for GSR**

**Individual Participant HR Histograms:** Following a visual inspection of the HR histograms, the following participants have been found to have HR spread of frequencies outside the normal interval of between 60 to 80.  Using the mean values, participant IDs 16, 24, 25, and 27 have some of the highest values while the other particiants in the Figure 5-39 Sensor Statistic Table Extract for HR have some of the lowest mean heart rate values.

| HR Sensor Statistics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ID | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max. | IQR | Variance | SD |
| 3 | 35.8862 | 46.0592 | 51.8895 | 52.8808 | 61.4186 | 77.5722 | 15.3594 | 107.0099 | 10.3446 |
| 9 | 44.1359 | 57.6372 | 60.9496 | 65.6638 | 73.8428 | 98.4570 | 16.2056 | 150.9259 | 12.2852 |
| 12 | 43.6344 | 52.6003 | 54.8546 | 55.2297 | 57.3108 | 76.9196 | 4.7105 | 20.7015 | 4.5499 |
| 16 | 54.0820 | 79.9963 | 85.3294 | 84.7297 | 93.6543 | 123.8653 | 13.6579 | 179.4024 | 13.3941 |
| 17 | 44.6491 | 56.9144 | 61.8077 | 63.4787 | 69.8188 | 87.2687 | 12.9044 | 65.6627 | 8.1032 |
| 20 | 47.9978 | 57.2665 | 60.9496 | 61.4954 | 67.8846 | 78.3638 | 10.6181 | 38.6487 | 6.2168 |
| 24 | 57.3108 | 73.8428 | 81.6984 | 81.7441 | 90.4615 | 109.7093 | 16.6187 | 97.7915 | 9.8890 |
| 25 | 49.8679 | 75.2907 | 82.4259 | 82.9841 | 87.2687 | 121.8727 | 11.9781 | 152.7108 | 12.3576 |
| 27 | 68.5683 | 79.9963 | 83.4744 | 84.7191 | 89.2982 | 119.9945 | 9.3019 | 49.9699 | 7.0689 |
| 29 | 47.4052 | 53.4676 | 55.1349 | 58.7947 | 59.9973 | 116.3583 | 6.5296 | 171.9418 | 13.1127 |
| 31 | 40.4192 | 51.1977 | 54.0820 | 55.7634 | 60.5034 | 91.4244 | 9.3058 | 56.9392 | 7.5458 |

**Figure 5-39 Sensor Statistic Table Extract for HR**

**Individual Participant IBI Histograms:** Following a visual inspection of the IBI plots the following participants in Figure 5-40 Sensor Statistic Table Extract for IBI have been found to have IBI spread of frequencies outside the normal interval of between 0.8 to 1.0. Using the mean IBI values, participant IDs 3, 9, 12, 17, 29, and 31 have some of the highest values while the other particiants in the figure have some of the lowest mean IBI values. Note that 16, 24, 25, and 27 had the highest mean HR and in the figure below they have some of the lowest mean IBI values.

| ID | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max. | IQR | Variance | SD |
|---|---|---|---|---|---|---|---|---|---|
| 3 | 0.8282 | 1.0804 | 1.1511 | 1.1951 | 1.3438 | 1.5626 | 0.2635 | 0.0289 | 0.1699 |
| 9 | 0.7084 | 0.8234 | 1.0127 | 0.9321 | 1.0435 | 1.0797 | 0.2200 | 0.0128 | 0.1131 |
| 12 | 0.9375 | 1.0568 | 1.0927 | 1.0828 | 1.1146 | 1.2188 | 0.0578 | 0.0030 | 0.0546 |
| 14 | 0.5636 | 0.7455 | 0.7801 | 0.7531 | 0.8025 | 0.9532 | 0.0571 | 0.0061 | 0.0782 |
| 16 | 0.5391 | 0.6654 | 0.6719 | 0.6800 | 0.6888 | 0.7891 | 0.0234 | 0.0014 | 0.0380 |
| 17 | 0.8230 | 0.9450 | 0.9782 | 0.9742 | 1.0157 | 1.0960 | 0.0707 | 0.0045 | 0.0669 |
| 24 | 0.5469 | 0.7348 | 0.7451 | 0.7408 | 0.7735 | 0.8397 | 0.0387 | 0.0029 | 0.0541 |
| 25 | 0.6250 | 0.7400 | 0.7537 | 0.7688 | 0.7754 | 1.2032 | 0.0354 | 0.0039 | 0.0623 |
| 27 | 0.6133 | 0.6953 | 0.7196 | 0.7138 | 0.7412 | 0.8125 | 0.0459 | 0.0012 | 0.0350 |
| 29 | 0.5313 | 1.0532 | 1.0688 | 1.0602 | 1.0973 | 1.1623 | 0.0441 | 0.0081 | 0.0901 |
| 31 | 0.7794 | 0.9965 | 1.0448 | 1.0494 | 1.1372 | 1.2813 | 0.1407 | 0.0093 | 0.0965 |
| 33 | 0.7344 | 0.7627 | 0.7791 | 0.7806 | 0.8027 | 0.8399 | 0.0400 | 0.0005 | 0.0229 |

**Figure 5-40 Sensor Statistic Table Extract for IBI**

**Individual Participant Temperature Histograms:** Following a visual inspection of the participants histogram data, the skin temperature ranges between 30 and 34 degrees for the majority of participants. There are a mixture of distributions for participants in the temperature histograms. A number of participants had a skin temperature over 34 and have some of the highest mean temperature values as represented in Figure 5-41 Sensor Statistic Table Extract for Temperature. These were participant IDs 2, 6, 9, 12, and 33. Participant IDs 13, 22, and 26 had some of the lowest temperature mean values.

| ID | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max. | IQR | Variance | SD |
|---|---|---|---|---|---|---|---|---|---|
| 2 | 32.7300 | 33.0500 | 33.0900 | 33.3214 | 33.6186 | 34.0500 | 0.5686 | 0.1101 | 0.3319 |
| 6 | 33.5586 | 33.9207 | 34.0300 | 34.0258 | 34.1700 | 34.3900 | 0.2493 | 0.0392 | 0.1979 |
| 9 | 32.1014 | 32.5114 | 33.0186 | 33.3278 | 34.2900 | 34.8014 | 1.7786 | 0.8666 | 0.9309 |
| 12 | 32.7186 | 32.8986 | 33.0167 | 33.0734 | 33.2487 | 33.5500 | 0.3501 | 0.0505 | 0.2248 |
| 13 | 30.0814 | 30.1900 | 30.2948 | 30.2892 | 30.3214 | 30.6353 | 0.1314 | 0.0181 | 0.1347 |
| 22 | 29.2171 | 29.5100 | 29.8028 | 29.7948 | 30.0158 | 30.6500 | 0.5058 | 0.1192 | 0.3452 |
| 26 | 29.0300 | 29.3720 | 29.5837 | 29.7497 | 30.3014 | 30.6004 | 0.9295 | 0.2434 | 0.4934 |
| 33 | 33.8586 | 34.0278 | 34.3986 | 34.3830 | 34.5500 | 35.0614 | 0.5222 | 0.0908 | 0.3013 |

**Figure 5-41 Sensor Statistic Table Extract for Temperature**

### 5.5.2 Micro Classification by Sensor Reporting and Analysis

As part of the statistical reporting on the participant individual datasets, box plots were produced for the emotions (Emotion), experiment groups (ExpGroup), and the experiment IDs (ExpID) classifications. For each of the three classifications on the individual participant datasets, five sets of thirty three box plots were produced for each of the E4 sensor data streams.

The following sections present reporting and analysis under the three classifications and discuses findings in relation to the GSR, Log GSR, HR, IBI, and Temperature data streams. The actual box plots in relation to this reporting and analysis section are not reproduced here but are available in the statistical appendices document volume 2 of 2 of this thesis.

**Emotions (Emotion) by sensor, reporting and analysis:** This section discusses the emotion classification by all four sensors across each participant's individual dataset generated from the original total master dataset. Reporting, observations and analytical discussion summaries are provided in the following top level analytics of the box plots produced for the emotion classification for each sensor data stream.

**Box plots of Emotion by GSR/Log GSR for all participant IDs:** The log GSR box plots were inspected visually. The median values primarily stayed the same across all seven emotions for the majority of participants. A number of participants had some degree of variation in their log GSR values. These were observed at participant IDs 2, 23, and 25.

**Box plots of Emotion by HR for all participant IDs:** For the classification of emotions by HR, the box plots did not reveal any consistent variations for each emotion. The box plots of participant IDs 3, 9, 16, 23, and 25 are different from other box plots as they have variance in their medians and IQRs across the emotion classifications. The HR values for these participants fluctuate considerably across all of the emotion classifications

**Box plots of Emotion by IBI for all participant IDs:** Similar to the HR sensor data stream there is no major variance in the IBI data at an individual level for emotion classification. Most of the box plots had very close median values for the seven emotions. The median values visibly vary up and down the IBI scale. The following participant IDs have box plots where the IQRs and median values had visible levels of variance. These are for participant IDs 3, 5, 7, 9, 12, 14, 17, 18, 20, 23, 26, and 31.

**Box plots of Emotion by Temperature for all participant IDs:** For the majority of participants the medians remained the same across the emotion classifications. The median varied up and down the temperature scale for each participant. The box plots for participant IDs 9, 14, 24, and 29 showed some variation in terms of their IQRs and medians.

**Experiment Group (ExpGroup) by sensor, reporting and analysis:** This section presents experiment group classification by all four sensors across each participant's individual dataset generated from the original total dataset. Reporting, observations and analytical discussion summaries are provided in the following top level analytics of the box plots produced for the experiment group classifications for each sensor data stream.

**Box plots of Experiment Group (ExpGroup) by GSR/Log GSR for all participants**: There are variances across the experiment groups but they are not clearly visible and in most cases are at the fractional change level. In a number of cases the E01 object manipulation experiments group has a slightly larger median value for a number of participants. In a number of other cases the median values for the E02 cognitive recall experiments is the group with the larger median values.

No major differences were identified across the median values for groups E03, E04, and E06. While there is certainly variance across the groups for each participant no clear patterns were identifiable across the sample population as a whole. Participant IDs 2, 7, 8, 9, 12, 23, 25, and 31 visibly appear to have interesting variance across their respective experiment groups.

**Box plots of Experiment Group (ExpGroup) by HR for all participants:** The HR medians do vary somewhat for the experiments thematic groups across the sample population. With the exception of a number of participants there are no dramatic changes across the groups. The majority of the experiment groups are in the 60 to 80 HR range but there are a number of exceptions where the experiment group has caused a spike in a specific participant's box plot.

HR median spikes were identified in the following experiment group(s) for the following participant IDs. Participant ID 5 for E06; ID 9 for E02; ID 14 for E06; ID 16 for E04, and ID 23 for E01. Participant IDs 12 and 31 had unusually low HR medians across the five experiment groups while participant IDs 25 and 27 had unusually high HR medians across the experiment groups.

**Box plots of Experiment Group (ExpGroup) by IBI for all participants:** Similar to the HR analysis there is visible variation in the IBI medians for the experiment groups but the changes are more subtle. The following participant IDs had some small visible median spikes for specific groups. Participant ID 7 for E03, ID 9 for E02, ID 14 for E06, ID 16 for E04, ID 23 for E01, and ID 29 for E04.

The IBI median variation for participant IDs 9, 14, 16, and 23 match the groups identified under the HR box plot analysis. Also visibly observed was the fact that participant IDs 12 and 31 had relatively high values for their IBI medians while IDs 25 and 27 were found to have lower median values across the experiment groups. This is in contrast to the trends reported for their respective HR medians.

**Box plots of Experiment Group (ExpGroup) by Temperature for all participants:** From a visual analysis there are clear variations in the medians across the experiment groups and the changes in the skin temperature are more visible across the groups for individual participants. As expected there were no major spikes in the skin temperature.

No general pattern was identifiable across the sample population in relation to the experiment thematic groups. That said, there is variance at the individual level and it can be demonstrated that the different groups of experiments made fractional changes to the participant's skin temperature as they participated in the randomly organised groups of experiments.

The following participant IDs box plots clearly demonstrate the variance in the skin temperature across the experiment groups. See box plots for participant IDs 1, 4, 8, 9, 10, 11, 14, 17, 18, 19, 23, 24, 25, 26, 28, 29, 30, and 31.

**Experiment ID (ExpID) by sensor, reporting and analysis:** This section presents experiment ID classification by all four sensors across each participant's individual dataset generated from the original total master dataset. Reporting, observations and analytical discussion summaries are provided in the following top level analytics of the box plots produced for the experiment ID classifications for each sensor data stream.

**Box plots of Experiment ID (ExpID) by GSR/Log GSR for all participants:** Log GSR did change in value across all the nineteen experiments for the majority of participants. Slight variation in the medians can be identified across the five experiment groups. Do note that the order of the experiments was randomised so this is a factor to be considered in the validation of the actual variation across the experiment groups. In a number of the box plots the median values are lower for the E02 group of experiments which involved positive and negative recall.

For the E01 object interaction experiments, the log GSR median values increase in slight step changes for a number of participants across the four tasks they had to carry out. The image experiments E03 tended to have slight fluctuations in their median as the experiments progressed. In a number of cases there was little visible change. In others there was either a slight step up or down in values. It was also visibly observed that the cat video, E03-PA, showed the most variation for the sample group. In certain cases, it was either higher or lower to the other log GSR median values.

The olfactory experiments visually appear to have very close medians for all five smell experiments, but on closer inspection there are slight identifiable changes in terms of downwards or upwards movement over the five values. There are some exceptions where there is clear variation and specifically in the case of participant IDs 23 and 25. For E06 the median values for both experiments are extremely close for the majority of the participants.

**Box plots of Experiment ID (ExpID) by HR for all participants:** Overall the participant HR varied across the experiments. For most, the HR varied for participants in E01 across the four object manipulation experiments. For E02 cognitive recall, the HR median was raised for the first experiment relating to negative recall. The opposite applied for the positive recall experiment, E02-PB, with the majority of participants showing a reduction in the HR medians. The third experiment was varied as the cognitive recall could be negative or positive and this is generally reflected in the box plots.

From visual analysis of the E03 box plots there is variation across all five experiments for the majority of participants. There are slight fluctuations that are visible as the experiments progressed. This is also the case for the olfactory experiments with medians changing across the five experiments for each individual. For the computer stress based experiments in E06, the Stroop experiment (E06-PA) had median values over and above the reaction speed test (E06-PB) median values for the majority of participant box plots.

**Box plots of Experiment ID (ExpID) by IBI for all participants:** The IBI generally shows a slightly waving line across all of the nineteen experiments. The IBI medians are all quite close to each other with no major variance across the experiments. For participant ID 3 there is a marked increase in IBI medians for E02 cognitive recall experiments group. Also in relation to E02 experiments, for participants ID 9 and 26 there is a marked decrease in the median IBI values. One other exception noticed was for participant ID 29 for the E04 olfactory experiments. The IBI was very low for the first experiment (E04-PA) and then increased continually as the experiments progressed.

**Box plots of Experiment ID (ExpID) by Temperature for all participants:** Skin temperature varies for all participants and it visibly changes for a good number of participants as they take part in the AC experiments. For E01 object manipulation there is a step increase in skin temperature primarily upwards as the majority of participants carry out all four experiments. For some, there is a minor increase but for others there are clearly identified step changes.

For quite a number of participants, the three E02 cognitive recall experiments visibly indicate that there has been a change in skin temperature during the experiments. In most cases the skin temperature dips down but in a few others it has increased in median values.

With reference to the imagery experiments in group E03, they can also be clearly identified in a number of participant box plots and they stand out noticeably in certain cases. From the visual inspection of a number of participant box plots, the skin temperature is up for the first experiment (E03-PA) for the cat video and it then drops down for the remaining four experiments of Disgust, Fear, Sadness, and Relaxed/Content imagery.

The majority of the E04 olfactory experiments saw no major variance in skin temperature medians for the majority of participants. One main exception was participant ID 11 which started off for E04-PA as a high skin temperature. This then reduced down as the other four experiments were carried out.

Recorded skin temperature varied across all participants for E06. The medians varied across both experiments but only slightly and in a lot of cases they visibly appeared equal.

This chapter section has presented micro reporting and analysis across individual participant datasets produced from the experiments overall total master dataset. The first section presented reporting and analysis on individual participant sensor statistics and related histograms based on the E4 sensor data streams. It also provided reporting and analysis across the classifications of Emotion, ExpGroup and ExpID for the E4 sensor data streams. The main summary findings and conclusions of the micro reporting and analysis from this section will be revisited and provided in the closing section of this chapter.

As a result of the macro and micro evaluations carried out, it was decided in conjunction with the CIT Department of Mathematics and Statistics that the experiments total master dataset should be investigated further using specialised statistical methods and techniques. The investigatory work that was conducted on the total master dataset is discussed in the next section of this chapter.

## 5.6 Applied Statistical Evaluation: Methods and Techniques

This section provides a general overview of the applied statistical evaluation investigations that were conducted on the AC experiments total master dataset. It then provides four specific evaluation sections that use generalized linear mixed models with specific focus on emotion classification.

### 5.6.1 Applied Statistical Evaluation: Work Overview

The statistical reporting and analysis investigations for the evaluation phases of the research were conducted under the guidance and direction of the CIT Department of Mathematics and Statistics and specifically in consultation with Dr. Catherine Palmer.

Having produced both the macro and micro statistics across the total master dataset and after conducting investigations on the data using the Emotion, ExpGroup, ExpID and the participant ID classifications, it was decided to conduct further work involving applied statistical techniques. As part of this applied approach, work was conducted into Principal Component Analysis (PCA) (Martins, 2013) as a means of reducing dataset complexity. The PCA approach investigated did not offer any major additional insights on the total master dataset and an alternative statistical method was to be found.

As the work on the macro and micro statistical reporting and analysis progressed there were indications that the mixture of classifications across emotion, experiments groups, experiment identities and the participant identities were having a significant effect on the results. With this in mind, Dr. Palmer proposed that the Generalized Linear Mixed Models using Template Model Builder[18]

[18] https://cran.r-project.org/web/packages/glmmTMB/index.html

(glmmTMB) (Magnusson, et al., 2017) statistical modelling package was worth investigating and applying to the experiments dataset.

In order to reduce the complexity of this work, the following assumptions were discussed, agreed upon and then applied to the glmmTMB statistical investigations.

**Assumption 01:** Evidence from the macro and micro analysis confirms that both Fear (approximately 2.3% of the total emotion classifications) and Surprise (approximately 3.8% of the total emotion classifications) would have minimum impact if their associated observations were deleted from the experiments total master dataset.

**Assumption 02:** The emotion classification of Contempt was discussed with Dr. Palmer. Past experimentation with the EmotionViewer adaptor has indicated that Contempt is recorded when there are no other visible emotional expressions on a subject's face. With this in mind and for the purposes of the glmmTMB modelling and statistical analysis it was agreed that the emotion classification Contempt was to be used as a control in the glmmTMB model.

**Assumption 03:** The four remaining emotion classifications of Joy, Disgust, Sadness, and Anger are to be applied to four separate glmmTMB models using the emotion classification of Contempt as a control in the model.

**Assumption 04:** The focus of the glmmTMB investigations are to be exclusively on the emotion classification as it relates to the overall thesis hypothesis.

**Assumption 05:** Considering the inverse correlation relationship between HR and IBI it is not to be considered in the glmmTMB analytics.

**Assumption 06:** While the Log GSR was used in the macro and micro reporting and analysis sections only the raw GSR data will be used in the glmmTMB analytical investigations.

**R software for glmmTMB:** The R software environment for statistical computing and graphics (The R Foundation, 2018) and the RStudio integrated development environment (IDE) for R (RStudio, 2018) was used throughout all of the statistical reporting and analysis work. The R code produced for the glmmTMB research work generally provided the following functionality.

- Loading of all required R libraries.
- Reading in the total master dataset.
- Removing the Fear and Surprise emotion observations from the dataset.
- Converting the categorical variables (Emotion, ExpGroup, ExpID and ID) to factors.
- Filtering the dataset to only one of the four emotion of Joy, Disgust, Sadness, and Anger while configuring Contempt as the control emotion for the glmmTMB model.
- Scaling the continuous variables of GSR, HR and Temperature in the dataset
- Fitting the data features to the various glmmTMB models.
- Summarising the glmmTMB models results.
- Conducting an analysis of variance (ANOVA) across selected stepwise reduced glmmTMB models.

The above R code processes were adjusted as required to apply the glmmTMB statistical algorithm across all four emotions using Contempt as a control.

**Using the glmmTMB model:** The glmmTMB processing and evaluation used involved a two way outcome approach. With this in mind, the emotions of Joy, Disgust, Sadness and Anger were each individually investigated using the glmmTMB package with the emotion of Contempt acting as the control in the modelling approach.

This sub-section has provided a general overview of the applied statistical work that was conducted especially in relation to glmmTMB methods and techniques. The next four sub-sections present results for the models along with general discussion. The overall findings and conclusions of the glmmTMB research work is provided in the section Applied Statistical Evaluation: Findings and Conclusions.

### 5.6.2 Generalized Linear Mixed Models: Joy and Contempt

This section presents the mixed models statistical reporting and analysis on the Joy and Contempt emotions. Firstly, the Joy and Contempt emotion observations were extracted from the total master dataset to create a filtered dataset. This filtered dataset was modelled using glmmTMB. The original mixed model contained all original feature variables. This model also incorporated two random effect intercepts which accounted for by participant identity (ID) variation and by experiment identity (ExpID) variation.

The complete mixed effects model that was used is represented below.

- **Emotion~E4_gsrX + E4_hrX + E4_temperatureX + ExpGroup + (1|ID) + (1|ExpGroup:ExpID)**

Models were selected using stepwise deletion and results from any fixed effects that were retained have been reported. Confidence interval (CI) and analysis of variance (ANOVA) results were produced and analysed at each stepwise deletion stage of the mixed effects model investigations. Where effects are reported in the results, both the parameter estimates and the standard errors are provided.

The Figure 5-42 Generalized Linear Mixed Models - Joy and Contempt represents highlight results of the statistical modelling that was conducted using the glmmTMB package.

For the glmmTMB statistical evaluation the ***p*** values were used to identify feature variable selection for the stepwise reduction. The identifiers '**fit**' refers to the complete mixed effects model and '**fit2**' refers to the stepwise adjusted model after the stepwise reduction process.

The two feature variables identified for the stepwise reduction from the starting conditional model table were E4_temperatureX (Temperature) and E4_hrX (HR). E4_temperatureX was removed for the first stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of the E4_temperatureX feature variable did not have any significant effect (***p = 0.9382***).

E4_hrX was removed for the second stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of the E4_hrX feature variable also did not have any significant effect (***p = 0.1629***).

Both E4_temperatureX and E4_hrX were then both removed for the third stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of the E4_temperatureX and E4_hrX feature variables also did not have any significant effect (***p = 0.3596***).

The stepwise reduction using the glmmTMB revealed that both the E4_temperatureX and E4_hrX may be removed from the model without any major significant loss of sensitivity and specificity.

| Starting Conditional Model Joy - Contempt | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | 1.812625 | 0.422951 | 0.98364104 | 2.64160896 | 4.286 | 1.82E-05 | | |
| E4_gsrX | 1.042208 | 0.071936 | 0.90121344 | 1.18320256 | 14.488 | <2e-16 | | |
| E4_hrX | 0.038497 | 0.027729 | -0.01585184 | 0.09284584 | 1.388 | 0.165 | | |
| E4_temperatureX | -0.005144 | 0.066355 | -0.1351998 | 0.1249118 | -0.078 | 0.938 | | |
| ExpGroupE02 | -1.673608 | 0.302393 | -2.26629828 | -1.08091772 | -5.535 | 3.12E-08 | | |
| ExpGroupE03 | -1.785224 | 0.266158 | -2.30689368 | -1.26355432 | -6.707 | 1.98E-11 | | |
| ExpGroupE04 | -0.08047 | 0.272756 | -0.61507176 | 0.45413176 | -0.295 | 0.768 | | |
| ExpGroupE06 | -1.490978 | 0.339741 | -2.15687036 | -0.82508564 | -4.389 | 1.14E-05 | | |
| | | | | | | | | |
| | | | | | | | | |
| ANOVA #1 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 9 | 15679 | 15748 | -7830.4 | 15661 | | | |
| fit | 10 | 15681 | 15758 | -7830.4 | 15661 | 0.006 | 1 | 0.9382 |
| | | | | | | | | |
| ANOVA #2 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 9 | 15681 | 15750 | -7831.4 | 15663 | | | |
| fit | 10 | 15681 | 15758 | -7830.4 | 15661 | 1.9474 | 1 | 0.1629 |
| | | | | | | | | |
| ANOVA #3 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 8 | 15679 | 15740 | -7831.4 | 15663 | | | |
| fit | 10 | 15681 | 15758 | -7830.4 | 15661 | 2.0455 | 2 | 0.3596 |
| | | | | | | | | |
| | | | | | | | | |
| Ending Conditional Model Joy - Contempt | | | | | | | | |
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | 1.80859 | 0.42287 | 0.9797648 | 2.6374152 | 4.277 | 1.89E-05 | | |
| E4_gsrX | 1.04699 | 0.07173 | 0.9063992 | 1.1875808 | 14.596 | <2e-16 | | |
| ExpGroupE02 | -1.67049 | 0.30294 | -2.2642524 | -1.0767276 | -5.514 | 3.50E-08 | | |
| ExpGroupE03 | -1.79086 | 0.26665 | -2.313494 | -1.268226 | -6.716 | 1.87E-11 | | |
| ExpGroupE04 | -0.08085 | 0.27317 | -0.6162632 | 0.4545632 | -0.296 | 0.767 | | |
| ExpGroupE06 | -1.48057 | 0.34022 | -2.1474012 | -0.8137388 | -4.352 | 1.35E-05 | | |

**Figure 5-42 Generalized Linear Mixed Models - Joy and Contempt**

The ending conditional model intercept estimates reveal that an increase in E4_gsrX (GSR) increases the log likelihood of the emotion Joy being present. The ExpGroup (various experiments groups with E01 used as a baseline in the glmmTMB) indicate that each of the different experiment groups E02 to E06 reduce the log likelihood of the emotion Joy being present.

All statistical analysis was conducted using R software version 3.4.3 (2017-11-30) and RStudio version 1.1.383 using the glmmTMB R package (Magnusson, et al., 2017).

A full set of results from the mixed effects model glmmTMB investigations of the Joy and Contempt emotions are provided in the thesis appendices volume 2 of 2.

### 5.6.3 Generalized Linear Mixed Models: Disgust and Contempt

This section presents the mixed models statistical reporting and analysis on the Disgust and Contempt emotions. Firstly, the Disgust and Contempt emotion observations were extracted from the total master dataset to create a filtered dataset. This filtered dataset was modelled using glmmTMB. The original mixed model contained all original feature variables. This model also incorporated two random effect intercepts which accounted for by participant identity (ID) variation and by experiment identity (ExpID) variation.

The complete mixed effects model that was used is represented below.

- **Emotion~E4_gsrX + E4_hrX + E4_temperatureX + ExpGroup + (1|ID) + (1|ExpGroup:ExpID)**

Models were selected using stepwise deletion and results from any fixed effects that were retained have been reported. Confidence interval (CI) and analysis of variance (ANOVA) results were produced and analysed at each stepwise deletion stage of the mixed effects model investigations. Where effects are reported in the results, both the parameter estimates and the standard errors are provided.

The Figure 5-43 Generalized Linear Mixed Models - Disgust and Contempt represents highlight results of the statistical modelling that was conducted using the glmmTMB package.

| Starting Conditional Model Disgust - Contempt | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | -0.605911 | 0.41778 | -1.4247598 | 0.2129378 | -1.45 | 0.14697 | | |
| E4_gsrX | -0.74916 | 0.079917 | -0.90579732 | -0.59252268 | -9.374 | <2e-16 | | |
| E4_hrX | 0.028199 | 0.033387 | -0.03723952 | 0.09363752 | 0.845 | 0.39832 | | |
| E4_temperatureX | -0.256215 | 0.096384 | -0.44512764 | -0.06730236 | -2.658 | 0.00785 | | |
| ExpGroupE02 | -0.348085 | 0.252511 | -0.84300656 | 0.14683656 | -1.378 | 0.16805 | | |
| ExpGroupE03 | 0.009604 | 0.221543 | -0.42462028 | 0.44382828 | 0.043 | 0.96542 | | |
| ExpGroupE04 | 0.457833 | 0.236773 | -0.00624208 | 0.92190808 | 1.934 | 0.05316 | | |
| ExpGroupE06 | 0.238484 | 0.279182 | -0.30871272 | 0.78568072 | 0.854 | 0.39298 | | |
| | | | | | | | | |
| | | | | | | | | |
| ANOVA #1 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 6 | 10318 | 10363 | -5153.3 | 10306 | | | |
| fit | 10 | 10318 | 10391 | -5148.8 | 10298 | 9.0272 | 4 | 0.06042 |
| | | | | | | | | |
| ANOVA #2 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 9 | 10316 | 10382 | -5149.1 | 10298 | | | |
| fit | 10 | 10318 | 10391 | -5148.8 | 10298 | 0.7105 | 1 | 0.3993 |
| | | | | | | | | |
| ANOVA #3 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 5 | 10317 | 10354 | -5153.6 | 10307 | | | |
| fit | 10 | 10318 | 10391 | -5148.8 | 10298 | 9.7258 | 5 | 0.08339 |
| | | | | | | | | |
| | | | | | | | | |
| Ending Conditional Model Disgust - Contempt | | | | | | | | |
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | -0.52972 | 0.39472 | -1.3033712 | 0.2439312 | -1.342 | 0.17959 | | |
| E4_gsrX | -0.74436 | 0.07962 | -0.9004152 | -0.5883048 | -9.349 | <2e-16 | | |
| E4_temperatureX | -0.26566 | 0.09625 | -0.45431 | -0.07701 | -2.76 | 0.00578 | | |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |

**Figure 5-43 Generalized Linear Mixed Models - Disgust and Contempt**

For the glmmTMB statistical evaluation the ***p*** values were used to identify feature variable selection for the stepwise reduction. The identifiers '**fit**' refers to the complete mixed effects model and '**fit2**' refers to the stepwise adjusted model after the stepwise reduction process.

The two feature variables identified for the stepwise reduction from the starting conditional model table were ExpGroup (Experiment groups) and E4_hrX (HR).

ExpGroup was removed for the first stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of the ExpGroup feature variable did not have any significant effect (***p = 0.06042***).

E4_hrX was removed for the second stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of the E4_hrX feature variable also did not have any significant effect (***p = 0.3993***).

Both ExpGroup and E4_hrX were removed for the third stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of both ExpGroup and E4_hrX feature variables did not have any significant effect (***p = 0.08339***).

The stepwise reduction using the glmmTMB revealed that both the ExpGroup and E4_hrX may be removed from the model without any major significant loss of sensitivity and specificity.

The ending conditional model intercept estimates reveal that a reduction in E4_gsrX (GSR) reduces the log likelihood of the emotion Disgust being present. A reduction in E4_temperatureX (Temperature) also reduces the log likelihood of the emotion Disgust being present.

All statistical analysis was conducted using R software version 3.4.3 (2017-11-30) and RStudio version 1.1.383 using the glmmTMB package (Magnusson, et al., 2017).

A full set of results from the mixed effects model glmmTMB investigations of the Disgust and Contempt emotions are provided in the thesis appendices volume 2 of 2.

### 5.6.4 Generalized Linear Mixed Models: Sadness and Contempt

This section presents the mixed models statistical reporting and analysis on the Sadness and Contempt emotions. Firstly, the Sadness and Contempt emotion observations were extracted from the total master dataset to create a filtered dataset. This filtered dataset was modelled using glmmTMB. The original mixed model contained all original feature variables. This model also incorporated two random effect intercepts which accounted for by participant identity (ID) variation and by experiment identity (ExpID) variation.

The complete mixed effects model that was used is represented below.

- **Emotion~E4_gsrX + E4_hrX + E4_temperatureX + ExpGroup + (1|ID) + (1|ExpGroup:ExpID)**

Models were selected using stepwise deletion and results from any fixed effects that were retained have been reported. Confidence interval (CI) and analysis of variance (ANOVA) results were produced and analysed at each stepwise deletion stage of the mixed effects model investigations. Where effects are reported in the results, both the parameter estimates and the standard errors are provided.

The Figure 5-44 Generalized Linear Mixed Models - Sadness and Contempt represents highlight results of the statistical modelling that was conducted using the glmmTMB package.

| Starting Conditional Model Sadness - Contempt | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | -1.72914 | 0.4621 | -2.634856 | -0.823424 | -3.742 | 0.000183 | | |
| E4_gsrX | 0.57035 | 0.08319 | 0.4072976 | 0.7334024 | 6.856 | 7.08E-12 | | |
| E4_hrX | -0.01022 | 0.03865 | -0.085974 | 0.065534 | -0.264 | 0.791428 | | |
| E4_temperatureX | 0.50372 | 0.08776 | 0.3317104 | 0.6757296 | 5.74 | 9.48E-09 | | |
| ExpGroupE02 | 0.86459 | 0.25977 | 0.3554408 | 1.3737392 | 3.328 | 0.000874 | | |
| ExpGroupE03 | 0.49929 | 0.23254 | 0.0435116 | 0.9550684 | 2.147 | 0.031784 | | |
| ExpGroupE04 | 0.82077 | 0.25208 | 0.3266932 | 1.3148468 | 3.256 | 0.00113 | | |
| ExpGroupE06 | 0.6073 | 0.28814 | 0.0425456 | 1.1720544 | 2.108 | 0.035059 | | |
| | | | | | | | | |
| | | | | | | | | |
| ANOVA #1 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 9 | 9971.7 | 10038 | -4976.9 | 9953.7 | | | |
| fit | 10 | 9973.7 | 10047 | -4976.8 | 9953.7 | 0.0701 | 1 | 0.7912 |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| Ending Conditional Model Sadness - Contempt | | | | | | | | |
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | -1.73067 | 0.46219 | -2.6365624 | -0.8247776 | -3.744 | 0.000181 | | |
| E4_gsrX | 0.57001 | 0.0832 | 0.406938 | 0.733082 | 6.851 | 7.32E-12 | | |
| E4_temperatureX | 0.50873 | 0.08569 | 0.3407776 | 0.6766824 | 5.937 | 2.91E-09 | | |
| ExpGroupE02 | 0.86737 | 0.25969 | 0.3583776 | 1.3763624 | 3.34 | 0.000838 | | |
| ExpGroupE03 | 0.50348 | 0.23211 | 0.0485444 | 0.9584156 | 2.169 | 0.030075 | | |
| ExpGroupE04 | 0.82258 | 0.2521 | 0.328464 | 1.316696 | 3.263 | 0.001103 | | |
| ExpGroupE06 | 0.60901 | 0.28821 | 0.0441184 | 1.1739016 | 2.113 | 0.034592 | | |

**Figure 5-44 Generalized Linear Mixed Models - Sadness and Contempt**

For the glmmTMB statistical evaluation the ***p*** values were used to identify feature variable selection for the stepwise reduction. The identifiers '**fit**' refers to the complete mixed effects model and '**fit2**' refers to the stepwise adjusted model after the stepwise reduction process.

The feature variable identified for the stepwise reduction from the starting conditional model table was E4_hrX (HR).

E4_hrX was removed for the stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of the E4_hrX feature variable did not have any significant effect (***p = 0.7912***).

The stepwise reduction using the glmmTMB revealed that E4_hrX may be removed from the model without any major significant loss of sensitivity and specificity.

The ending conditional model intercept estimates reveal that an increase in E4_gsrX (GSR) increases the log likelihood of the emotion Sadness being present. An increase in E4_temperatureX (Temperature) also increases the log likelihood of the emotion Sadness being present. The ExpGroup (various experiments groups with E01 used as a baseline in the glmmTMB) indicate that each of the different experiment groups E02 to E06 increase the log likelihood of the emotion Sadness being present.

All statistical analysis was conducted using R software version 3.4.3 (2017-11-30) and RStudio version 1.1.383 using the glmmTMB R package (Magnusson, et al., 2017).

A full set of results from the mixed model glmmTMB investigations of the Sadness and Contempt emotions are provided in the thesis appendices volume 2 of 2.

### 5.6.5 Generalized Linear Mixed Models: Anger and Contempt

This section presents the mixed models statistical reporting and analysis on the Anger and Contempt emotions. Firstly, the Anger and Contempt emotion observations were extracted from the total master dataset to create a filtered dataset. This filtered dataset was modelled using glmmTMB. The original mixed model contained all original feature variables. This model also incorporated two random effect intercepts which accounted for by participant identity (ID) variation and by experiment identity (ExpID) variation.

The complete mixed effects model that was used is represented below.

- **Emotion~E4_gsrX + E4_hrX + E4_temperatureX + ExpGroup + (1|ID) + (1|ExpGroup:ExpID)**

Models were selected using stepwise deletion and results from any fixed effects that were retained have been reported. Confidence interval (CI) and analysis of variance (ANOVA) results were produced and analysed at each stepwise deletion stage of the mixed effects model investigations. Where effects are reported in the results, both the parameter estimates and the standard errors are provided.

The Figure 5-45 Generalized Linear Mixed Models - Anger and Contempt represents highlight results of the statistical modelling that was conducted using the glmmTMB package.

| Starting Conditional Model Anger - Contempt | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | -0.22026 | 0.36782 | -0.9411872 | 0.5006672 | -0.599 | 0.54928 | | |
| E4_gsrX | 0.02441 | 0.0482 | -0.070062 | 0.118882 | 0.506 | 0.61251 | | |
| E4_hrX | 0.15068 | 0.03484 | 0.0823936 | 0.2189664 | 4.325 | 1.53E-05 | | |
| E4_temperatureX | 0.14635 | 0.06693 | 0.0151672 | 0.2775328 | 2.187 | 0.02877 | | |
| ExpGroupE02 | -0.11312 | 0.31354 | -0.7276584 | 0.5014184 | -0.361 | 0.71826 | | |
| ExpGroupE03 | 0.26934 | 0.27543 | -0.2705028 | 0.8091828 | 0.978 | 0.32812 | | |
| ExpGroupE04 | 0.47762 | 0.28704 | -0.0849784 | 1.0402184 | 1.664 | 0.09612 | | |
| ExpGroupE06 | 0.99543 | 0.35137 | 0.3067448 | 1.6841152 | 2.833 | 0.00461 | | |
| | | | | | | | | |
| | | | | | | | | |
| ANOVA #1 | Df | AIC | BIC | logLik | deviance | Chisq | ChiDf | Pr(>Chisq) |
| fit2 | 9 | 13852 | 13920 | -6917.1 | 13834 | | | |
| fit | 10 | 13854 | 13929 | -6917 | 13834 | 0.2562 | 1 | 0.6127 |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| Ending Conditional Model Anger - Contempt | | | | | | | | |
| | Estimate | Std.Error | CI Low | CI High | zValue | Pr(>\|z\|) | | |
| (Intercept) | -0.21671 | 0.36772 | -0.9374412 | 0.5040212 | -0.589 | 0.55563 | | |
| E4_hrX | 0.15194 | 0.03477 | 0.0837908 | 0.2200892 | 4.369 | 1.25E-05 | | |
| E4_temperatureX | 0.14295 | 0.06658 | 0.0124532 | 0.2734468 | 2.147 | 0.03179 | | |
| ExpGroupE02 | -0.11412 | 0.31399 | -0.7295404 | 0.5013004 | -0.363 | 0.71627 | | |
| ExpGroupE03 | 0.26507 | 0.27571 | -0.2753216 | 0.8054616 | 0.961 | 0.33635 | | |
| ExpGroupE04 | 0.47607 | 0.28741 | -0.0872536 | 1.0393936 | 1.656 | 0.09764 | | |
| ExpGroupE06 | 0.99602 | 0.35189 | 0.3063156 | 1.6857244 | 2.83 | 0.00465 | | |

**Figure 5-45 Generalized Linear Mixed Models - Anger and Contempt**

For the glmmTMB statistical evaluation the ***p*** values were used to identify feature variable selection for the stepwise reduction. The identifiers '**fit**' refers to the complete mixed effects model and '**fit2**' refers to the stepwise adjusted model after the stepwise reduction process.

The feature variable identified for the stepwise reduction from the starting conditional model table was E4_gsrX (GSR).

E4_gsrX was removed for the stepwise reduction. A two-way ANOVA with test = ***Chisq*** was conducted on both models. The ANOVA results revealed that the removal of the E4_gsrX feature variable did not have any significant effect (***p = 0.6127***).

The stepwise reduction using the glmmTMB revealed that E4_gsrX may be removed from the model without any major significant loss of sensitivity and specificity.

The ending conditional model intercept estimates reveal that an increase in E4_hrX (HR) increases the log likelihood of the emotion Anger being present. An increase in E4_temperatureX (Temperature) also increases the log likelihood of the emotion Anger being present. The ExpGroup (various experiments groups with E01 used as a baseline in the glmmTMB) indicate that each of the different experiment groups E03, E04 and E06 increase the log likelihood of the emotion Anger being present. Note that the experiment group E02 reduces the log likelihood of the emotion Anger being present.

All statistical analysis was conducted using R software version 3.4.3 (2017-11-30) and RStudio version 1.1.383 using the mixed effects glmmTMB R package (Magnusson, et al., 2017).

A full set of results from the mixed model glmmTMB investigations of the Anger and Contempt emotions are provided in the thesis appendices volume 2 of 2.

This concludes the applied statistical investigations using generalized linear mixed models across the emotion classification. The overall findings and conclusions in relation to the glmmTMB modelling work from the above four sections will be discussed in the next final section of chapter five.

## 5.7 Experiments Evaluation Overall Findings and Conclusions

This section summaries the main findings of the previous three sections and also provides a number of conclusions related to the thesis hypothesis. The overall findings and conclusions sub-sections will follow the same order as the previous three sections presented.

### 5.7.1 Macro Statistical Evaluation: Findings and Conclusions

This part revisits the macro statistical evaluation section of chapter five and presents a summary of the key findings from the various reporting and analysis discussions along with a number of thesis hypothesis related conclusions.

The main findings and conclusions of the Macro Bar Plots of Classification Possibilities section are listed below:

- There are 36,748 data observations in the total master experiments dataset that can be analysed by Emotion, ExpGroup, ExpID, and by participant ID.
- The emotions of Fear (839 observations at 2.3%) and Surprise (1,401 observations at 3.8%) are identified as having very low classification numbers.
- Experiment E06 (11,267 observations at 30.7%) has the largest number of recorded observations.

- Experiment E04 (2,859 observations at 7.8%) has the lowest number of recorded observations.

**Conclusions 01:**

- Fear and Surprise observations identified by the EmotionViewer adaptor are both extremely low.
- From conducting the experiments, the number of recorded observations are an accurate reflection of the actual duration of the various groups of experiments.

The main findings and conclusions of the Macro Histograms for Sensor Data Streams, reporting and analysis section are listed below:

- **GSR/Log GSR:** The raw GSR sensor has micro changes between 0 and 1 with the first and third quartiles ranges from 0.21 to 0.91 across all of the experiments. See page 184 and 185 in thesis volume 2 of 2.
- **GSR/Log GSR:** The Figure 5-17 Histogram Log Galvanic Skin Response (GSR) demonstrates how the raw GSR was converted into a normal distribution. Also see page 185 in thesis volume 2 of 2.
- **HR:** HR has a normal distribution from 45 to 100. See page 186 in thesis volume 2 of 2.
- **IBI:** The IBI is negatively correlated with the HR sensor data and is separately computed from the E4 PPG data. See page 186 in thesis volume 2 of 2.
- **Temperature:** The Temperature sensor ranges from 30 to 36 and has first and third quartiles of 30.78 and 33.26. See page 184 and 187 in thesis volume 2 of 2.

**Conclusions 02:**

- Transforming the GSR to the Log GSR produced a typical normal data distribution.
- The IBI negative correlation with the HR can be used to validate findings in relation to the HR data streams.

The main findings and conclusions of the Emotions (**Emotion**) by Sensors, reporting and analysis section are listed below:

- **GSR/Log GSR:** For the log GSR data values, there is statistical variance for the emotions minimum and maximum values and there are identifiable difference in their IQR and median values. All these values are provided on page 200 in thesis volume 2 of 2.
- **GSR/Log GSR:** The log GSR median variances are clearly identified across Anger (-0.75), Contempt (-0.89), and Disgust (-1.06) and there are also median variance identifiable in the Joy (-0.91) and Sadness (-1.34) emotion classifications. See page 200 in thesis volume 2 of 2.
- **GSR/Log GSR:** Fear and Surprise have variation but are of less significance due to the low number of observations by the EmotionViewer.
- **HR:** The HR data values do not reflect any major variance in the median values across all emotion classifications. Anger (71.77), Contempt (72.47), Disgust (72.23), Fear (71.23), Joy (71.14), Sadness (73.84), and Surprise (70.46). See page 200 in thesis volume 2 of 2.
- **IBI:** The IBI does not appear to add any additional insights to the emotion classifications. Median values are Anger (0.82), Contempt (0.82), Disgust (0.81), Fear (0.82), Joy (0.83), Sadness (0.82), and Surprise (0.83). See page 200 in thesis volume 2 of 2.

- **Temperature:** Anger (median 32.06, first quartile 30.65, and third quartile 33.02) and Disgust (median 32.09, first quartile 30.63, and third quartile 33.07) appear to be very similar in terms of their IQR and their median values. See page 200 in thesis volume 2 of 2.
- **Temperature:** Contempt shows the lowest median value (31.91) across all of the emotions classified.
- **Temperature:** For Joy and Sadness, the median for Joy (32.42) is higher than that of Sadness (32.26).

**Conclusions 03:**

- The Log GSR box plot demonstrates statistical variance across the seven emotions that were identified by the EmotionViewer.
- HR and IBI do not show any significant statistical variance across the seven emotions.
- Temperature shows specific statistical variance across a number of the emotion classifications.

The main findings and conclusions of the Experiment Groups (**ExpGroup**) by Sensors, reporting and analysis section are listed below:

- **GSR/Log GSR:** The log GSR medians are on a downwards trajectory for experiment groups E01 to E04. E01 (-0.77), E02 (-0.94), E03 (-1.09), and E04 (-1.16). See page 191 and 201 in thesis volume 2 of 2.
- **Temperature:** The Temperature box plot clearly demonstrates that the E03 imagery group of experiments has a drop in skin temperature across the population sample with the skin temperature at its lowest with a median value of 31.89. See page 201 in thesis volume 2 of 2.

- **Temperature:** The E04 olfactory group of experiments has the next lowest median skin temperature with a median value of 32.14. See page 201 in thesis volume 2 of 2.

**Conclusions 04:**

- Both Log GSR and Temperature show specific statistical variance across selected groups of experiments.
- HR and IBI have not shown any significant statistical variance in relation to the experiment groups.

The main findings and conclusions of the Experiment IDs (**ExpID**) by Sensors, reporting and analysis section are listed below and can also be referenced in thesis volume 2 of 2 on pages 202 to 206:

- **GSR/Log GSR:** The normal GSR data demonstrates minimum statistical variance across experiments and also has a considerable number of outliers. See page 194 in thesis volume 2 of 2.
- **GSR/Log GSR:** Using the log GSR, for E01 the values are raised for the last two experiments on the Vaseline tin (-0.60) and the mouse trap (-0.36).
- **GSR/Log GSR:** In E02 the first negative recall experiment produced a lower log GSR median (-1.01) than the next experiment on positive recall (-0.89).
- **HR:** The HR median was down for E01-PB which was the metal puzzle task. From E01-PA (73.14) to E01-PB (70.46).
- **HR:** For E02-PA on negative recall the HR median was raised (73.84) and then down for the positive recall E02-PB (71.10).

- **HR:** HR median values fell for both the muscle strain cream E04-PB (from 73.84 to 69.36) and also for the drain cleaner E04-PD (from 70.47 to 69.33) negative smells.
- **HR:** For experiment group E06, the HR medians (E06-PA 75.29 and E06-PB 72.44) are the polar opposite of the log GSR median values (E06-PA -0.95 and E06-PB -0.86).
- **IBI**: For E01 the median is higher for the mouse trap experiment (0.83) than the other three experiments in the group (0.81, 0.82, and 0.81).
- **IBI**: The IBI median is the lowest of all five for the muscle strain cream E04-PB (0.82).
- **IBI**: The IBI median for the drain cleaner E04-PD (0.85) is actually the highest of all five olfactory experiments.
- **Temperature:** There is a significant median difference between E01-PA (31.77) and E01-PB (32.50).
- **Temperature:** For E02 the negative recall experiment E02-PA (32.18) shows a reduction in the skin temperature median.
- **Temperature:** For the cat video E03-PA (32.41) and the disgust images E03-PB (32.37) the median for both are almost identical.
- **Temperature:** The temperature median significantly reduced for the fear images E03-PC (31.54) experiment.
- **Temperature:** The median increased again for the sadness images E03-PD (31.92) and for the final images of relaxation and contentment E03-PE (31.87).
- **Temperature:** For E04 the medians were similar for the first two experiments (32.13, 32.17), they were reduced on the coconut smell E04-PC (31.85) and the drain cleaner smell E04-PD (31.80). The median

recovered again across the sample population for the final positive lavender and patchouli smell E04-PE (32.19).

**Conclusions 05:**

- Log GSR ExpID box plots show specific statistical variance for certain experiments in E01 and E02 groups of experiments.
- HR ExpID box plots show statistical variance for specific experiments in E01, E02, E04 and E06 groups of experiments.
- IBI ExpID box plots show statistical variance for specific experiments in E01 and E04 groups of experiments.
- Temperature ExpID box plots show statistical variance for specific experiments in E01, E03 and E04 groups of experiments.
- All sensors picked up specific statistical variance in the macro analysis of the ExpID data.
- In particular experiment group E01 demonstrated statistical variance for the ExpIDs from all four physiological sensors.

The main findings and conclusions of the Box Plots Participant IDs (**ID**) by Sensor, reporting and analysis are listed below and can also be referenced in thesis volume 2 of 2 on pages 207 to 213:

- **GSR/Log GSR:** Using the -4 to +2 log GSR scale it is clear that there are significant GSR responses for all 33 participants. For example AC-006 (1.46) and AC-007 (-1.75); AC-023 (-2.63) and AC-024 (1.40).
- **HR:** There is considerable variance across all 33 participants for the HR data. For example AC-015 (70.02) and AC-016 (85.32); AC-028 (73.59) and AC-029 (55.13).

- **IBI:** The IBI also shows variance across all of the sample population.
- **IBI:** Participant IDs AC-003 (1.15), AC-012 (1.09), AC-029 (1.06) and AC-031 (1.04) on the IBI box plots all have raised IBI values.
- **Temperature:** There is considerable variance across all 33 participants for the Temperature data. For example AC-008 (31.07) and AC-009 (33.01); AC-018 (30.91) and AC-019 (34.86).

**Conclusions 06:**

- All four sensors report significant statistical variance in their respective box plots at the individual participant ID level.

The main findings and conclusions of the Macro Vision and Geneva Emotion Wheel (**GEW**) Analysis, reporting and analysis are listed below:

- **Experiments group E01 dexterity based object interactions:** From both the EmotionViewer and the GEW self-reporting classification plots the correlation of both positive and negative emotions across the four E01 experiments has been identified.
- **Experiments group E02 cognitive based:** From both the EmotionViewer and the GEW self-reporting classification plots, negative emotions are evident for the first experiment, positive emotions are evident for the second experiment and the third experiment is a mix of positive and negative emotions.
- **Experiments group E03 visual based:** GEW self-reporting plots are closely matched with the EmotionViewer for four of the E03 experiments

with the exception being E03-PE, where the EmotionViewer classified negative emotions, where positive emotions were expected.

- **Experiments group E04 olfactory based:** The GEW self-report reflects the expected emotional responses for the olfactory experiments. The EmotionViewer classifications did not correlate with the GEW classifications.
- **Experiments group E06 gaming based:** Overall the self-report data demonstrates a mixed set of emotions. This is also reflected in the EmotionViewer classifications where primarily negative emotions dominate along with a significant presence of the Joy emotion classification.
- A further quantification exercise was conducted on the EmotionViewer and the GEW self-reporting datasets. Details can be found in thesis volume 2 of 2 on pages 214 to 218. This quantification exercise involved a reduction of the twenty GEW emotions to match the seven EmotionViewer classifications along with accounting for the overall response percentage of emotional reporting by all participants. In thesis volume 2 of 2, page 218 provides a table that compares the GEW emotion classifications with the camera EmotionViewer emotion classifications. The following emotion classifications percentages were calculated, Anger (GEW 10.52%, EmotionViewer 10.07 %), Contempt (GEW 1.88, EmotionViewer 8.48%), Disgust (GEW 11.82%, EmotionViewer 7.95%), Fear (GEW 2.74%, EmotionViewer 1.06%), Joy (GEW 50.35%, EmotionViewer 15.90%), Sadness (GEW 10.93%, EmotionViewer 7.42%), and Surprise (GEW 10.83%, EmotionViewer 2.12%).

**Conclusions 07:**

- Both the EmotionViewer dataset and the GEW self-reporting dataset demonstrate classification correlation in the reported statistical results for the E01, E02 and E06 groups of experiments.
- Both the EmotionViewer dataset and the GEW self-reporting dataset demonstrate classification correlation in the reported statistical results for the E03 group of experiments with the exception of the final E03-PE experiment where the EmotionViewer picked up excessive negative emotion classifications.
- The EmotionViewer dataset and the GEW dataset reported statistical results did not demonstrate classification correlation for the olfactory E04 group of experiments.
- The quantification exercise demonstrates that the GEW and EmotionViewer emotion classifications variance for Anger is 0.45%, Disgust is 3.87%, Fear is 1.68% and Sadness is 3.51% and are each within small percentile difference ranges.

### 5.7.2 Micro Statistical Evaluation: Findings and Conclusions

This sub-section revisits the micro statistical evaluation section of chapter five and presents a summary of the key findings from the various reporting and analysis discussions along with a number of thesis hypothesis related conclusions.

The main findings and conclusions of the Micro Sensor Statistics and Histograms, reporting and analysis are listed below and can also be referenced in thesis volume 2 of 2 on pages 219 to 224:

- **GSR/Log GSR:** Eight of the participants had a mean raw GSR rate over 1.0.
- **GSR/Log GSR:** Strong degree of variance in raw GSR data was reported for participant IDs AC-002, AC-006, AC-009, AC-012, AC-017, AC-024, AC-027, and AC-033, see page 223.
- **HR:** Across the sample population, the mean HR spread was from 52.88 to 84.72, see page 220.
- **IBI:** Means are similar for individual participants but there is still a unique mean value for each participant, see page 221 in thesis volume 2 of 2.
- **HR/IBI:** Participant IDs AC-016 (HR 84.72, IBI 0.68), AC-024 (HR 81.74, IBI 0.74), AC-025 (HR 82.98, IBI 0.76) and AC-027 (HR 84.71, IBI 0.71) had the highest mean HR and some of the lowest mean IBI values. See pages 223 and 224 in thesis volume 2 of 2.
- **Temperature:** For skin temperature, the mean values range from 29.74 to 35.11.
- **Temperature:** Standard deviation (SD) value differences are into fractional changes and require four decimal places at least to identify SD variance across individuals for the skin temperature data stream.
- **Temperature:** Skin temperature value ranges between 30 and 34 degrees for approximately 52% of the participant group.
- **Temperature:** A number of participants have high mean temperature values. For example for participant IDs AC-002 (33.32), AC-006 (34.02), AC-009 (33.32), AC-012 (33.07), and AC-033 (34.38).
- **Temperature:** Participant IDs AC-013 (30.28), AC-022 (29.79), and AC-026 (29.74) had some of the lowest temperature mean values.

**Conclusions 08:**

- 25% of participants showed a strong degree of statistical variance in their GSR data.
- High HR mean values are associated with low IBI mean values.
- Skin Temperature changes at a fractional level across the participant sample population.
- There are extremes of high (AC-011 36.81) and low (AC-026 29.03) skin temperature for a number of participants.

The main findings and conclusions of the Emotion **(Emotion)** by Sensors, reporting and analysis are listed below:

- **GSR/Log GSR:** The log GSR median values primarily stayed the same across all seven emotions for approximately 88% of the participants.
- **GSR/Log GSR:** Participant IDs AC-002, AC-009, AC-023, and AC-025 have specific statistical variance in their respective log GSR values. See thesis volume 2 of 2 pages 247 to 251.
- **HR:** Box plots for approximately 85% of participants did not reveal any significant statistical variance in HR for each emotion.
- **HR:** Participant IDs AC-003, AC-009, AC-016, AC-023 and AC-025 have identified variance in their medians and IQRs. Their HR values fluctuate considerably across all of the emotion classifications. See thesis volume 2 of 2 pages 252 to 256.
- **IBI:** Approximately 64% of the box plots have visibly close median values across all of the seven emotions.
- **IBI:** Participant IDs AC-003, AC-005, AC-007, AC-009, AC-012, AC-014, AC-017, AC-018, AC-020, AC-023, AC-026, and AC-031 have IQRs and

median values with specific statistical variance at approximately 36%. See thesis volume 2 of 2 pages 257 to 261.

- **Temperature:** For approximately 88% of participants the skin temperature median values demonstrated minimum statistical variance across the emotion classifications.
- **Temperature:** Participant IDs AC-009, AC-0014, AC-024, and AC-029 showed specific degrees of statistical variance in terms of their IQRs and medians. See thesis volume 2 of 2 pages 262 to 266.

**Conclusions 09:**

- The GSR, HR and Temperature sensors have demonstrated minimum statistical variance across the individual Emotion box plots for participants. As identified above, certain exceptions were identified in the box plots of all three sensors.
- The IBI sensor data demonstrated the most statistical variance across approximately 36% of the participant box plots.

The main findings and conclusions of the Experiment Group **(ExpGroup)** by Sensors, reporting and analysis are listed below:

- **GSR/Log GSR:** Participant IDs AC-002, AC-007, AC-008, AC-009, AC-012, AC-023, AC-025, and AC-031 demonstrate specific statistical variance (24%) across their experiment group box plots. See thesis volume 2 of 2 pages 273 to 277.
- **HR:** Approximately 85% of experiment groups are in the 60 to 80 HR range. There are a number of participant exceptions where the experiment group has caused a HR spike.

- **HR:** HR median spikes were identified for participant AC-005 for E06 (80 – 100); AC-009 for E02 (80 – 100); AC-014 for E06 (80 – 100); AC-016 for E04 (40 – 60), and AC-023 for E01 (80 – 100). See thesis volume 2 of 2 pages 278 to 282.
- **IBI:** The following participant IDs had some minor visible median spikes for specific groups. Participant AC-007 for E03 (0.8 – 1.0), AC-009 for E02 (0.6 – 0.8), AC-014 for E06 (0.6 – 0.8), AC-016 for E04 (0.6 – 0.8), AC-023 for E01 (0.6 – 0.8), and AC-029 for E04 (0.8 – 1.0).
- **IBI/HR:** The IBI median variation for participant IDs AC-009, AC-014, AC-016, and AC-023 match the groups identified under the HR box plot analysis E02, E06, E04, and E01 respectively. See thesis volume 2 of 2 pages 283 to 287.
- **Temperature:** There are clear variations in the medians across the experiment groups at the individual level for approximately 55% of the participant box plots.
- **Temperature:** Participant IDs AC-001, AC-004, AC-008, AC-009, AC-010, AC-011, AC-014, AC-017, AC-018, AC-019, AC-023, AC-024, AC-025, AC-026, AC-028, AC-029, AC-030, and AC-031 demonstrate statistical variance in their skin temperature data across selected experiment thematic groups.
- **Temperature:** At the individual level, the groups of experiments made fractional change to the participant's skin temperature as they participated in the randomly organised groups of experiments.
- **Temperature:** No general pattern could be identified in relation to the experiment thematic groups across all of the participant box plots. See thesis volume 2 of 2 pages 288 to 292.

**Conclusions 10:**

- 24% of participants showed statistical variance in their GSR data across the experiment groups
- HR and IBI statistical data varied for a number of participants on specific groups of experiments.
- Negative correlation between HR and IBI is further confirmed.
- Skin Temperature changed as participants carried out each group of experiments.
- Approximately 55% of participants have clearly demonstrated statistical variance in their reported skin temperature data.

The main findings and conclusions of the Experiment ID **(ExpID)** by Sensors, reporting and analysis are listed below:

- **GSR/Log GSR:** The Log GSR median values demonstrate statistical variance across a number of the nineteen experiments for approximately 73% of participant box plots. Statistical variance is identified in the following participant box plots, AC-002, AC-006, AC-007, AC-008, AC-009, AC-010, AC-011, AC-012, AC-013, AC-014, AC-015, AC-016, AC-017, AC-018, AC-021, AC-022, AC-023, AC-024, AC-025, AC-026, AC-027, AC-028, AC-031, and AC-032.
- **GSR/Log GSR:** In participant box plots AC-001, AC-013, AC-014, AC-015, AC-016, AC-020, and AC-033, the median values are lower for the E02 group of experiments.
- **GSR/Log GSR:** For the E01 object interaction experiments, the log GSR median values show statistical variance for approximately 61% of the participant box plots across the four tasks. E01 statistical variance is

demonstrated in the following participant box plots, AC-001, AC-002, AC-003, AC-009, AC-010, AC-012, AC-013, AC-014, AC-016, AC-017, AC-021, AC-023, AC-024, AC-025, AC-026, AC-028, AC-030, AC-031, AC-032, and AC-033.

- **GSR/Log GSR:** For the E03 image experiments, the cat video, E03-PA, demonstrated statistical variance across approximately 58% of the thematic group. In a number of cases it was either higher or lower to the other log GSR median values in the E03 group. E03-PA statistical variance is demonstrated in the following participant box plots, AC-003 AC-005, AC-007, AC-008, AC-009, AC-010, AC-011, AC-012, AC-014, AC-015, AC-016, AC-017, AC-018, AC-021, AC-023, AC-024, AC-025, AC-029, and AC-033.
- **GSR/Log GSR:** For the EO4 olfactory experiments, there is minor statistical variance in terms of downwards or upwards movement over the five sensor experiment values in approximately 52% of participant box plots. E04 minor statistical variance is demonstrated in the following participant box plots, AC-002, AC-004, AC-006, AC-007, AC-008, AC-010, AC-011, AC-012, AC-013, AC-015, AC-016, AC-017, AC-018, AC-021, AC-023, AC-025, and AC-027.
- **GSR/Log GSR:** For the E06 experiments the median values for both experiments are extremely close for approximately 82% of the participant box plots. E06 median similarity is demonstrated in the following participant box plots, AC-001, AC-002, AC-003, AC-004, AC-005, AC-006, AC-007, AC-009, AC-010, AC-011, AC-012, AC-013, AC-014, AC-015, AC-017, AC-019, AC-020, AC-021, AC-022, AC-024, AC-027, AC-028,

AC-029, AC-030, AC-031, AC-032, and AC-033. See thesis volume 2 of 2 pages 299 to 303.

- **HR:** For 100% of participant box plots the, HR medians demonstrated statistical variance across all of the experiments.
- **HR:** For approximately 76% of participant box plots, the HR median varied across the four object manipulation experiments in E01. E01 statistical variance is demonstrated in the following participant box plots, AC-001, AC-002, AC-004, AC-005, AC-008, AC-009, AC-011, AC-012, AC-013, AC-014, AC-015, AC-016, AC-017, AC-019, AC-021, AC-022, AC-024, AC-025, AC-026, AC-027, AC-028, AC-030, AC-031, AC-032, and AC-033.
- **HR:** For E02-PA negative cognitive recall, the HR median was raised in approximately 55% of participant box plots. E02-PA statistical variance for negative cognitive recall is demonstrated in the following participant box plots, AC-001, AC-002, AC-004, AC-009, AC-010, AC-012, AC-013, AC-015, AC-018, AC-019, AC-022, AC-024, AC-025, AC-026, AC-027, AC-029, AC-030, and AC-031.
- **HR:** For E02-PB positive cognitive recall, the HR median was reduced in approximately 52% of participant box plots. E02-PB statistical variance for positive cognitive recall is demonstrated in the following participant box plots, AC-001, AC-002, AC-004, AC-009, AC-010, AC-012, AC-013, AC-015, AC-018, AC-019, AC-022, AC-024, AC-025, AC-026, AC-027, AC-029, and AC-030.
- **HR:** The E03 participant box plots demonstrate statistical variance across all five experiments for approximately 82% of participants. E03 statistical variance is demonstrated in the following participant box plots, AC-001,

AC-003, AC-004, AC-005, AC-006, AC-007, AC-008, AC-009, AC-010, AC-011, AC-012, AC-013, AC-014, AC-015, AC-016, AC-018, AC-019, AC-020, AC-022, AC-024, AC-025, AC-027, AC-029, AC-030, AC-031, AC-032, and AC-033.

- **HR:** The E04 olfactory experiments demonstrate median values changing across the five experiments for approximately 61% of participant box plots. E04 statistical variance is demonstrated in the following participant box plots, AC-001, AC-002, AC-004, AC-006, AC-010, AC-012, AC-013, AC-014, AC-015, AC-019, AC-020, AC-021, AC-024, AC-025, AC-027, AC-028, AC-029, AC-031, AC-032, and AC-033.
- **HR:** The Stroop test experiment (E06-PA) had median values that were greater than the reaction speed test (E06-PB) median values for approximately 73% of participant box plots. This E06 statistical variance in both experiments is demonstrated in the following participant box plots, AC-001, AC-002, AC-005, AC-007, AC-009, AC-010, AC-011, AC-012, AC-013, AC-014, AC-015, AC-017, AC-018, AC-019, AC-020, AC-021, AC-022, AC-025, AC-026, AC-027, AC-028, AC-029, AC-030, and AC-031. See thesis volume 2 of 2 pages 304 to 308.
- **IBI:** The IBI sensor data stream values demonstrate minimum statistical variance in approximately 94% of participant box plots. The two exceptions are the box plots for participants AC-003 and AC-029. See thesis volume 2 of 2 pages 309 to 313.
- **Temperature:** Skin temperature statistical variance is demonstrated in approximately 79% of participant box plots as they complete the various experiments. Skin temperature statistical variance is demonstrated in the following participant box plots, AC-001, AC-003, AC-004, AC-005, AC-

008, AC-009, AC-010, AC-011, AC-012, AC-014, AC-015, AC-017, AC-018, AC-019, AC-021, AC-022, AC-023, AC-024, AC-025, AC-026, AC-027, AC-028, AC-029, AC-030, AC-031, and AC-033.

- **Temperature:** For E01 object manipulation there is observed statistical variance in the form of an increase in skin temperature for approximately 82% of participant box plots. For some this is a minor increase but for others there are clearly identified significant changes in skin temperature. For E01 experiments skin temperature, statistical variance is demonstrated in the following participant box plots, AC-001, AC-002, AC-004, AC-005, AC-008, AC-009, AC-010, AC-013, AC-014, AC-015, AC-016, AC-017, AC-019, AC-020, AC-021, AC-022, AC-023, AC-024, AC-025, AC-026, AC-027, AC-028, AC-029, AC-030, AC-031, AC-032, and AC-033.
- **Temperature:** The three E02 cognitive recall experiments visibly indicate that there has been a change in skin temperature during the experiments in approximately 42% of participant box plots. For E02 experiments skin temperature, statistical variance is demonstrated in the following participant box plots, AC-002, AC-005, AC-008, AC-009, AC-010, AC-011, AC-016, AC-017, AC-018, AC-021, AC-022, AC-025, AC-026, and AC-029.
- **Temperature:** For E03 the skin temperature is up for the first experiment (E03-PA) for the cat video. It then drops down for the remaining four experiments of Disgust, Fear, Sadness, and Relaxed/Content imagery for approximately 30% of participant box plots. For the E03 experiments this type of skin temperature statistical variance is demonstrated in the

following participant box plots, AC-005, AC-010, AC-011, AC-012, AC-015, AC-017, AC-023, AC-024, AC-025, and AC-032.

- **Temperature:** The E04 olfactory experiments saw no significant statistical variance in skin temperature medians for approximately 88% of the participant box plots.
- **Temperature:** Recorded skin temperature data varied across approximately 64% of participant box plots for both E06 experiments. The E06 median variance across both experiments are minor in a number of the following participant box plots, AC-001, AC-002, AC-003, AC-009, AC-010, AC-011, AC-012, AC-013, AC-015, AC-016, AC-017, AC-018, AC-019, AC-020, AC-021, AC-022, AC-024, AC-027, AC-028, AC-030, and AC-032. See thesis volume 2 of 2 pages 314 to 318.

**Conclusions 11:**

- The Log GSR data showed statistical variance for all nineteen experiments for approximately 73% of participant box plots. It also demonstrated statistical variance across individual experiments in the experiment groups.
- HR median values showed statistical variance across individual experiments in the experiment groups for 100% of participant box plots.
- IBI data demonstrated no major statistical variance across the individual experiment IDs.
- Approximately 79% of participants demonstrated statistical variance in their skin temperature data as they completed the experiments.
- There is statistical variance in skin temperature identified in participant box plots across all experiments in groups E01, E02, E03 and E06.

- There was no significant statistical variance identified in the skin temperature for participants when participating in the E04 olfactory group of experiments.

### 5.7.3 Applied Statistical Evaluation: Findings and Conclusions

This part revisits the applied statistical evaluation section of chapter five and presents a summary of the key findings from the various reporting and analysis discussions relating to glmmTMB modelling along with a number of thesis hypothesis related conclusions.

**Generalized Linear Mixed Models: Joy and Contempt**

- The stepwise reduction results indicated that the E4_temperatureX and E4_hrX feature variables could be removed for the Joy classification without any major significant loss of sensitivity and specificity.

**Conclusions 12:**

- Increases in the E4_gsrX (intercept 1.04699) data stream values indicate the increased probability of a Joy expression being present.
- Each of the experiment groups E02 (intercept -1.67049), E03 (intercept -1.79086), E04 (intercept -0.08085), and E06 (intercept -1.48057) reduced the probability of a Joy expression being present.

**Generalized Linear Mixed Models: Disgust and Contempt**

- The stepwise reduction results indicated that the ExpGroup and E4_hrX feature variables could be removed for the Disgust classification without any major significant loss of sensitivity and specificity.

**Conclusions 13:**

- Reduction in the E4_gsrX (intercept -0.74436) data stream values indicate the decreased probability of a Disgust expression being present.
- Reduction in the E4_temperatureX (intercept -0.26566) data stream values indicate the decreased probability of a Disgust expression being present.

**Generalized Linear Mixed Models: Sadness and Contempt**

- The stepwise reduction results indicated that the E4_hrX feature variable could be removed for the Sadness classification without any major significant loss of sensitivity and specificity.

**Conclusions 14:**

- Increases in the E4_gsrX (intercept 0.57001) data stream values indicate the increased probability of a Sadness expression being present.
- Increases in the E4_temperatureX (intercept 0.50873) data stream values indicate the increased probability of a Sadness expression being present.
- Each of the experiment groups E02 (intercept 0.86737), E03 (intercept 0.50348), E04 (intercept 0.82258), and E06 (intercept 0.60901) increased the probability of a Sadness expression being present.

**Generalized Linear Mixed Models: Anger and Contempt**

- The stepwise reduction results indicated that the E4_gsrX feature variable could be removed for the Anger classification without any major significant loss of sensitivity and specificity.

**Conclusions 15:**

- Increases in the E4_hrX (intercept 0.15194) data stream values indicate the increased probability of an Anger expression being present.
- Increases in the E4_temperatureX (intercept 0.14295) data stream values indicate the increased probability of an Anger expression being present.
- Each of the experiment groups E03 (intercept 0.26507), E04 (intercept 0.47607), and E06 (intercept 0.99602) increased the probability of an Anger expression being present.
- Experiment group E02 (intercept -0.11412) reduces the probability of an Anger expression being present.

This concludes the AC experiments evaluation chapter of the thesis. The next chapter provides a review of the overall thesis research contributions, final hypothesis related summary conclusions, outlooks and projections.

# 6 Thesis Contributions, Conclusions and Future Work

Chapter six is both reflective and forward looking, with four sections. The first section aims to summarise the overall AC research contributions resulting from the thesis as well as related disseminations associated with various research activities. Section two provides a summary of the main thesis hypothesis conclusions and revisits, from a consolidation perspective, the many problems and challenges the AC field is facing both in the present and into the future.

The third section on outlooks and projections provides updates and advances with reference to application domains, sensory technologies, and the dangers and threats of AI. This section also specifically addresses some of the more open issues and opportunities directly relating to the thesis research conducted. The concluding section four is an executive summary of the overall research that has been presented throughout this thesis.

## 6.1 Thesis Research Contributions and Disseminations

This section presents a highlight summary of the main contributions to the AC field that have been produced as a direct result of the thesis research that was conducted. This is then followed by a section that documents other contributions and dissemination activities that have also resulted from the thesis research.

### 6.1.1 Main Thesis Contributions

This section discusses a number of concrete deliverables and contributions from the thesis research that has been conducted. Each one is presented under a related heading and is discussed with reference to the various chapters of the thesis where further detail can be found.

**AC SoTA research:** The scientific and technological review in chapter two is a focal reference point for researchers new to AC and provides foundational insights into the role of psychology in AC. It also provides a comprehensive background into the scientific and technological aspects of unimodal and multi-modal AC sensory solutions. By its nature, AC is a multi-sensor, data fusion problem, the chapter two research also addresses multi-sensory data fusion methods, techniques, problems and challenges.

**AC domain related research:** Throughout the thesis, specific domain related research has been examined. These domain areas have been discussed primarily in chapters one and two and are also updated in this chapter. The thesis has had a main focus in the application of AC technologies to the eHealth domain. Applied use cases have been presented in chapter three and a number of domain related literature contributions have also been made (see below).

**AC conceptual architecture:** One of the main objectives of the thesis research was not only to develop AC related software, but to provide a conceptual foundation, thinking and architecture to any such software artifact developments. This conceptual architecture was presented in chapter three. The AC conceptual architecture is entrenched in the two S-Strata and AC-Strata stratification models that were also developed as part of the research. The conceptual architecture provides for the realisation of many advanced AC functionalities and should act as a central reference point for AC researchers in any future engineering and development efforts.

**EFS prototypical solution:** The EFS prototypical solution is the engineered result of the research into the AC conceptual architecture. The EFS is an evolving software platform that has been used extensively in the AC research experiments. It has also been a major contribution to the RISE SenseCare project architecture (see Figure 2-41 SenseCare Four Layer Architecture). The EFS software solution also provides prototype sensor adaptors for vision, wearables, PC inputs and BCI sensors.

**AC thesis ethics and experiments documentation:** As part of the formal AC experiments phases of the research, ethics processes had to be followed and documentation had to be created for all of the experiments that were conducted. Both the ethics proposal and all research experiments related documentation is available to future AC researchers as a reference point in preparation for their own experiments. This documentation is provided in the thesis appendices in volume 2 of 2.

**AC research datasets:** As explained in chapter five, a comprehensive set of AC related datasets were produced across the thirty three participants involved in the research. This total master dataset has been processed during the statistical reporting, analysis and evaluation stages of the research. This dataset can be sliced up into views based on emotion (Emotion), experiment group (ExpGroup), experiment identity (ExpID), and participant identity (ID) classifications. The total dataset can also be separated into just vision or wearables related datasets if required.

The GEW self-reporting dataset has also been compiled into a total master dataset across all participants. It can also be analysed based on the above classifications. The raw E4 sensor data has been produced and stored for each of the participants and is available for future related experiments and analysis as required by AC researchers.

**AC statistical reporting:** A set of comprehensive statistical reports have been produced in relation to the evaluation of the thesis research hypothesis. These include macro and micro statistics computations, statistics tables, histograms, bar plots, PCA explorations, ANOVA tests and applied statistical analysis using generalized linear mixed models (glmmTMB). A suite of R programs have also been developed for the reporting and analysis phases of the research. The full set of statistical reporting documentation can be found in thesis volume 2 of 2.

**Thesis research findings and conclusions:** The thesis evaluation process resulted in the identification of a number of hypothesis and AC related findings and conclusions. These are discussed in the next section of chapter six, Summary of Main Thesis Conclusions, Problems and Challenges.

**AC literature contributions:** A number of literature contributions have been made and disseminations conducted as a result of the research. See the next section for further details.

**AC futures, problems and challenges:** The state of the art research resulted in the identification of a comprehensive set of AC related problems and challenges. These problems and challenges have been audited and analysed across various modalities and from a data and sensory fusion perspective. These results are presented as a roadmap to the areas that AC needs to address in the future. They are documented in this chapter under the section on Identified Problems and Challenges.

**Indirect thesis contributions:**

- **AC researchers:** This thesis research has helped and inspired a number of early stage computer science researchers at the CIT SIGMA research centre.
- **SenseCare contributions:** A number of the above thesis contributions have furthered the overall SenseCare project and have also influenced the research work packages and deliverables across the project partnership.

### 6.1.2 Other Thesis Contributions and Disseminations

The thesis research conducted has already made a number of contributions and disseminations in relation to the AC field in terms of conference submissions and attendances, journal papers, book chapters, lectures/presentations, networking activities and EU research work. These contributions and disseminations are briefly summarised below under a number of related headings.

**EHealth, stress management and QS - Conferences**

The role of reproducibility in Affective Computing appliances: A case study presented at the IEEE International Conference on Bioinformatics and Biomedicine (BIBM) 2017 conference (Engel, Keary, Berwind, Bornschlegl, & Hemmje, 2017).

Preforming real-time emotion classification using an Intel RealSense camera, multiple facial expression databases and a Support Vector Machine presented at the Collaborative European Research Conference (CERC) 2017, (Healy, Keary, & Walsh, 2017).

Contributing author to paper on the visualisation of AC for emotional well-being of older people. Paper was presented at the EAI International Conference on Wearables in Healthcare, Budapest, Hungary, 2016 (Bond, et al., 2017).

Contributing author to paper on lifecycle management of clinical health care presented at the Collaborative European Research Conference (CERC), Cork, 2016 (Kowohl, et al., 2016).

Involved in the development of a prototype AC related platform for the tracking of agitation in elderly and dementia sufferers. Presented at the Collaborative European Research Conference (CERC), Cork, 2016, (Healy, Keary, & Walsh, 2016).

Presented SenseCare project overview and related AC sensory fusion at the Measuring Behaviour 2016 conference in Dublin, (Keary & Walsh, 2016). Abstract and poster presented.

Presented proof of concept of AC integration into a psychological based serious game via Unity at the 2015 conference on Brain Informatics and Health in London, (Keary, et al., 2015). Abstract, poster and presentation.

Presented AC research paper at the workshop on The Role of Quantified Self for Personal Healthcare (QSPH) held at the IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Belfast, 2014 (Keary & Walsh, 2014). Abstract, paper, poster, presentation at workshop, and applied discussion on AC and QS interrelationships.

## EHealth, stress management and QS - Journals

Journal paper on the SenseCare platform for home-based visualisation of emotional states of people with dementia. Published in Road Mapping Infrastructures for Advanced Visual Interfaces Supporting Big Data in Springer Lecture Notes in Computer Science, Springer, 2016 (Engel, et al., 2016).

## Games Based Learning (GBL) - Conferences

Presented at games based learning conferences on the potential of AC integration into games development. Abstracts, posters, papers and presentations involved.

- Presented at the Irish Symposium on Game Based Learning (iGBL), Cork, 2014 (Keary & Walsh, 2014).
- Presented at the Limerick Postgraduate Research Conference (LPRC), Limerick, 2014, (Keary & Walsh, 2014).
- Presented at the Collaborative European Research Conference (CERC), Cork, 2013, (Keary & Walsh, 2013).
- Presented at the Irish Symposium on Game Based Learning 2013 (iGBL), Dublin, 2013 (Keary, Walsh, O'Byrne, Moizer, & Lean, 2013).

## Games Based Learning (GBL) - Books

Book chapter on serious online role-playing games. Published in Game-Based Learning and the Power of Play: exploring evidence, challenges and future directions, Cambridge Scholars, 2016 (Keary, et al., 2016).

EBook documenting research from the EU S-Cube project on serious games published by University of Plymouth Press, 2014, (Asperges, et al., 2014).

**SenseCare EU RISE Project:** The following thesis research related contributions were made to the SenseCare EU RISE project.

- Lead author of SenseCare Work Package WP2, Deliverable 2.1 Requirements Analysis and Architecture for SenseCare AC Layer Version 1.0
- Contributing author to SenseCare WP1 Deliverable 1.1 Pilot Dementia Care and Connected Health Collection of Research Resources Report (Version 1.0)
- Contributing author to SenseCare WP3 Deliverable 3.1 Requirements and Architecture for SenseCare Data Fusion layer Version 1.0
- Contributing author to SenseCare WP3 Deliverable 3.2 Semantic and Ontological Notebook for SenseCare Data Fusion layer
- Contributing author to SenseCare WP4 Deliverable 4.1 Semantic and Ontological Notebook on Psychology of AC. Version 1.0
- Contributing author to SenseCare WP4 Deliverable 4.2 Psychology of AC SenseCare Portal Description. Version 1.0

Presentation of AC research work relating to SenseCare EU review meeting for WP2 on 24th April 2017.

- Presentation on requirements for engineering of software technologies to fuse together affective sensory data using affective computing methods and machine learning algorithms to deliver cognitive and emotional state data on a subject in real time.

**Other Related Contributions:**

**Human Computer Interaction Conference 2018:** Ongoing support to Ulster University in relation to organising and co-chairing the Affective Computing workshop scheduled to be held at the British Computer Society 32nd Human Computer Interaction Conference[19].

**AC research community:** Won an Irish Research Council New Foundations (Irish Research Council) grant to establish and run the Association for the Advancement of Affective Computing - Local Interest Group, Ireland. This is an all-Ireland group of researchers working and interested in AC and AS (Keary & Walsh, 2017).

**Visiting lecturer:** Presented a guest lecture on Affective Computing at the International Space University summer programme held at CIT in 2017 (Cork Institute of Technology (CIT), 2017).

Presented a guest lecture on AC to faculty staff and post-graduate students at Ulster University, Belfast campus in 2014.

**AC and Computer Mediated Communications (CMC):** Book chapter on current trends, developments, future requirements and predictions for computer mediated communications and e-collaboration. This chapter included research relating to AC and was published in Knowledge Discovery, Transfer, and Management in the Information Age, IGI – Global, 2013 (Keary, Redfern, & Walsh, 2013).

[19] http://hci2018.bcs.org/

Journal research paper on CMC, conferencing and collaboration. These platforms and technologies are candidates for the application and integration of AC and AS in the future. Published in the International Journal of e-Collaboration, 2012 (Keary & Redfern, 2012).

## 6.2 Summary of Main Thesis Conclusions, Problems and Challenges

The primary aim of this section is to present a consolidated summary and evaluation of the main thesis hypothesis conclusions that were produced from the evaluation work conducted for chapter five. Separately, it also further investigates the problems and challenges that have been identified in relation to AC science and technology throughout the various chapters of the thesis.

### 6.2.1 Main Thesis Conclusions

The thesis AC experiments were primarily conducted to evaluate the thesis hypothesis and the outlined objectives as documented in chapter one. Indirectly the AC experiments also acted as a major test environment for the software artifacts that make up the EFS prototypical platform solution.

Chapter five has provided extensive reporting, analysis, findings and conclusions across many aspects of the evaluations phases. Chapter five is also supported with the detailed statistical reporting appendices contained in volume 2 of 2. This section presents the overall thesis conclusions at a high-level and with specific association and discussion related to the thesis hypothesis $\boldsymbol{H^0}$. These thesis conclusions are presented in the same order of the summary findings and conclusions of chapter five.

**Macro statistical evaluation thesis conclusions:** The following high-level conclusions have been produced from the macro statistical reporting and analysis in chapter five.

- The emotions of Fear and Surprise did not suffice detailed investigation due to the minimum number of observations by the EmotionViewer.
- HR and IBI are negatively correlated.
- The log GSR was used to provide a more natural distribution of the GSR data streams.
- **Emotion classification:** GSR and Temperature has significant evidence of statistical variance.
- **Emotion classification:** HR and IBI do not provide significant evidence of statistical variance.
- **ExpGroup classification:** GSR and Temperature has significant evidence of statistical variance.
- **ExpGroup classification:** HR and IBI do not provide significant evidence of statistical variance.
- **ExpID classification:** GSR, Temperature, HR, and IBI sensors produce degrees of statistical variance.
- **ExpID classification:** Experiment E01 demonstrates major statistical variance across the four experiments conducted.
- **ID classifications:** GSR, Temperature, HR, and IBI sensors all report strong degrees of statistical variance.
- **EmotionViewer and GEW:** The results indicate that there is a high correlation and significant relationship between the EmotionViewer and GEW results for all experiments in groups E01, E02 and E06. This was

also confirmed for the experiments in group E03 with the exception of experiment E03-PE

- **EmotionViewer and GEW:** The results indicate that there is no correlation or significant relationship between the EmotionViewer and GEW results for the experiments in group E04.

**Macro evaluation - Hypothesis salient conclusions:** From the chapter five reporting and analysis sections, the related summary findings and conclusions, the original statistics in the appendices, and from the above distilled set of summarised macro evaluation conclusions the following hypothesis related salient conclusions are stated.

**Hypothesis salient conclusion 01:** In both the Emotion and ExpGroup classifications, the GSR and skin Temperature sensors produced significant evidence of statistical variance in the macro evaluation. For these classifications the HR and IBI sensors did not provide sufficient evidence of statistical variance in the macro evaluation.

**Hypothesis salient conclusion 02:** When the macro evaluation went deeper into the ExpID and the participant ID classifications, all four wearable sensor data streams produced significant evidence of statistical variance.

**Hypothesis salient conclusion 03:** The EmotionViewer produced classification results and statistics that have acute correlation accuracy with the GEW self-reporting results and statistics. This equates to approximately 74% (fourteen out of nineteen experiments) correlation accuracy for the EmotionViewer classifications across the total master dataset.

**Micro statistical evaluation thesis conclusions:** The following high-level conclusions have been produced from the micro statistical reporting and analysis in chapter five.

- There is approximately 25% statistical variance in the GSR data values for the sample population.
- If the HR mean is up then the IBI mean should be down for the same participant.
- Skin Temperature demonstrates fractional changes but has extremes of high and low values for some participants.
- **Emotion classification:** GSR, HR, and Temperature shows no evidence of any major significant statistical variance for the sample population.
- **Emotion classification:** IBI data values show significant statistical variance of approximately 36% for the sample population.
- **ExpGroup classification:** Temperature (55% approximately) and GSR (25% approximately) values demonstrated degrees of statistical variance for the sample population.
- **ExpGroup classification:** HR and IBI values demonstrated no significant statistical variance for the sample population.
- **ExpGroup classification:** Negative correlation of the HR and IBI was confirmed at the micro level.
- **ExpID classification:** GSR, HR and Temperature all demonstrate significant statistical variance for all nineteen experiments for the sample population and primarily for experiment groups E01, E02, E03, and E06.

- **ExpID classification:** Skin Temperature for the experiments in E04 did not demonstrate any major significant statistical variance for the sample population.
- **ExpID classification:** The IBI values did not demonstrate any significant statistical variance for all nineteen experiments for the sample population.

**Micro evaluation - Hypothesis salient conclusions:** From the chapter five reporting and analysis sections, the related summary findings and conclusions, the original statistics in the appendices, and from the above distilled set of summarised micro evaluation conclusions the following hypothesis related salient conclusions are stated.

**Hypothesis salient conclusion 04:** In the Emotion classification, the GSR, skin Temperature, and HR sensors did not provide sufficient evidence of statistical variance in the micro evaluation. For the Emotion classification, the IBI did show some evidence of statistical variance for a number of individual participants.

**Hypothesis salient conclusion 05:** In the ExpGroup classification, the GSR (25%) and skin Temperature (55%) sensors produced evidence of statistical variance in the micro evaluation. For the ExpGroup classification, the HR and IBI did not provide sufficient evidence of statistical variance in the micro evaluation.

**Hypothesis salient conclusion 06:** In the ExpID classification, the GSR, skin Temperature, and HR sensors produced evidence of significant statistical variance in the micro evaluation. For the ExpID classification, the IBI did not provide sufficient evidence of statistical variance in the micro evaluation.

**Applied statistical evaluation thesis conclusions:** The following high-level conclusions have been produced from the applied statistical evaluation reporting and analysis in chapter five.

The generalized linear mixed models (glmmTMB) investigations conducted in the applied statistical research phase provide reported evidence in justification of the following conclusions.

- **Joy:** Increased Joy is associated with increased GSR.
- **Joy:** Experiments in groups E02, E03, E04, and E06 are associated with reduced Joy.
- **Disgust:** Decreased Disgust is associated with a decrease in GSR.
- **Disgust:** Decreased Disgust is associated with a decrease in skin Temperature.
- **Sadness:** Increased Sadness is associated with increased GSR.
- **Sadness:** Increased Sadness is associated with increased skin Temperature.
- **Sadness:** Experiments in groups E02, E03, E04, and E06 are associated with increased Sadness.
- **Anger:** Increased Anger is associated with increased skin Temperature.
- **Anger:** Increased Anger is associated with increased HR.
- **Anger:** Experiments in groups E03, E04, and E06 are associated with increased Anger.
- **Anger:** Experiments in groups E02 are associated with reduced Anger.

**Applied evaluation - Hypothesis salient conclusions:** From the chapter five reporting and analysis sections, the related summary findings and conclusions, the original statistics in the appendices, and from the above distilled set of summarised applied evaluation conclusions the following hypothesis related salient conclusions are stated.

**Hypothesis salient conclusion 07:** Increased GSR is associated with increased Joy and Sadness emotions. Reduced GSR is associated with reduced Disgust emotion.

**Hypothesis salient conclusion 08:** Increased Temperature is associated with increased Sadness and Anger emotions. Reduced Temperature is associated with reduced Disgust emotion.

**Hypothesis salient conclusion 09:** Increased HR is associated with increased Anger emotion.

**Hypothesis salient conclusion 10:** Observations with the experiment groups E03, E04, and E06 classifications increased Sadness and Anger emotions. For the same classifications the emotion Joy was reduced.

**Hypothesis salient conclusion 11:** Observations with the experiment group E02 classification increased the Sadness emotion. The same E02 classification reduced the emotions of Joy and Anger.

### 6.2.2 Hypothesis Salient and Overall Conclusions

This section presents the salient conclusions from the macro, micro and applied statistical evaluations in the form of three graphical summaries. It also bolsters the overall statistical analytics with discussion and literature references already provided in the thesis chapters where appropriate. The thesis hypothesis is then revisited and discussed with reference to the statistical evidence presented and a decision relating to the acceptance or rejection of the null hypothesis (***$H^0$***) is provided.

**Hypothesis salient conclusions graphical summaries:** The figures discussed below use colour codes for explanation purposes. Red represents an entity increasing in value, blue represents an entity decreasing in value, and amber represent an entity that is neutral and is neither increasing nor decreasing in value.

| Macro Evaluation | Emotion | ExpGroup | ExpID | ID |
|---|---|---|---|---|
| Sensors | | | | |
| GSR | ↑ SV | ↑ SV | ↑ SV | ↑ SV |
| | | | | |
| Temperature | ↑ SV | ↑ SV | ↑ SV | ↑ SV |
| | | | | |
| HR | ↓ SV | ↓ SV | ↑ SV | ↑ SV |
| | | | | |
| IBI | ↓ SV | ↓ SV | ↑ SV | ↑ SV |

**Figure 6-1 Macro Evaluation - Hypothesis Salient Conclusions**

The macro evaluation graphic in Figure 6-1 Macro Evaluation - Hypothesis Salient Conclusions demonstrates that GSR and Temperature sensor values have increased statistical variance (SV) for the EmotionViewer Emotion classification.

In conclusion, based on the macro evaluation there is a significant statistical relationship between the E4 wearables adaptor GSR and Temperature sensors and the EmotionViewer vision adaptor. Other statistical relationships relating to emotions were also identified across the ExpGroup, ExpID and the ID classifications. There is no significant statistical relationship between the E4 wearables adaptor and the EmotionViewer vision adaptor for the HR sensor and IBI data streams.

| Micro (ID) Evaluation | Emotion | ExpGroup | ExpID |
|---|---|---|---|
| Sensors | | | |
| GSR | ↓ SV | ↕ SV | ↑ SV |
| | | | |
| Temperature | ↓ SV | ↑ SV | ↑ SV |
| | | | |
| HR | ↓ SV | ↓ SV | ↑ SV |
| | | | |
| IBI | ↕ SV | ↓ SV | ↓ SV |

**Figure 6-2 Micro Evaluation - Hypothesis Salient Conclusions**

The micro evaluation graphic in Figure 6-2 Micro Evaluation - Hypothesis Salient Conclusions demonstrates that GSR, Temperature, and HR sensor values have decreased SV for the overall Emotion classification. The seven Emotion classifications were not associated with significant changes in any of the three sensor ranges for the vast majority of participants. Note that in relation to select individuals, there is evidence of certain SV for a number of participants in their sample population box plots.

The ExpGroup has increased SV for Temperature while the ExpID classification demonstrates increased SV for GSR, Temperature and HR.

In conclusion, based on the micro evaluation there is no significant statistical relationship between the E4 wearable adaptor GSR, Temperature and HR sensors and the EmotionViewer vision adaptor for the majority of the participants in the sample population. The existence of high levels of SV, particularly at the ExpID level, indicates that the majority of the SV is due to the intense personalised nature of affect analytics at the individual participant level.

Overall, while the sensitivity and specificity of the wearables and vision adaptors at the micro level is a concern, the combined evidence with the macro evaluation in relation to the GSR and Temperature is certainly statistically significant.

| Applied Evaluation | Joy | Disgust | Sadness | Anger |
|---|---|---|---|---|
| Sensors | | | | |
| GSR ↑ | ↑ | NA | ↑ | NA |
| GSR ↓ | NA | ↓ | NA | NA |
| | | | | |
| Temperature ↑ | NA | NA | ↑ | ↑ |
| Temperature ↓ | NA | ↓ | NA | NA |
| | | | | |
| HR↑ | NA | NA | NA | ↑ |
| ExpGroup | | | | |
| E02 | ↓ | NA | ↑ | ↓ |
| E03 | ↓ | NA | ↑ | ↑ |
| E04 | ↓ | NA | ↑ | ↑ |
| E06 | ↓ | NA | ↑ | ↑ |

**Figure 6-3 Applied Evaluation - Hypothesis Salient Conclusions**

The Figure 6-3 Applied Evaluation - Hypothesis Salient Conclusions summarises the applied glmmTMB conclusions with four emotions and their related sensor states. As the sensors increase or decrease in data values, this leads to an increased or decreased log likelihood of a particular emotion being present. While the macro and micro evaluations have provided valid findings, the mixed effect modelling provided deeper insights into the sensitivity and specificity aspects of the vision and wearables adaptors.

The above provides further support for both the GSR and Temperature sensors relationship with the Emotion classifications and how changes are reflected by the increased log likelihood of a particular emotion's presence in an individual.

The literature has discussed how increased GSR is associated with high arousal while decreased GSR is associated with low arousal (Picard , Fedor, &

Ayzenberg , 2016). In relation to the above figure, one could argue for high GSR for Joy as an indicator of high arousal but Sadness does not generally fall into a high arousal category. This may be explained by the work of Sakr et al. (Sakr, Elhajj, & Huijer, 2010) who discussed how high stress is associated with high levels of GSR and the fact that Sadness (incorporating feelings of loneliness) is a stress related emotion. Also interesting is that the fall is GSR reduces the log likelihood of the Disgust emotion which could be attributed to a movement from a high arousal state to a lower state of arousal of less Disgust.

According to the above figure, the emotions of Sadness and Anger are associated with increases in skin temperature, while a reduction in levels of Disgust is associated with a reduction in skin temperature values. These findings are interesting and perhaps merit further research with reference to the work of Sakr et al. (Sakr, Elhajj, & Huijer, 2010) who have also found skin temperature to reduce as stress levels increase. Researching the link between stress and the emotions of Sadness, Anger and Disgust may offer valuable insights in relation to the development and validation of physiological based emotion datasets.

In the literature, Wen et al. discussed how they discovered that GSR and HR have common intra-class affective patterns (Wen, et al., 2014), [p. 126]. HR has been found to have certain statistical significance in the thesis hypothesis investigations but it certainly has not been as dominant at the GSR and Temperature sensors throughout all of the evaluation phases. The identified increase in HR values associated with the increased log likelihood of Anger being present was the main finding for HR. The HR was removed as a non-significant feature variable in the other emotions modelling research as part of the stepwise reduction processes.

The ExpGroup findings provide supporting evidence to the emotion classifications. The evidence of increased Sadness and Anger for E03, E04 and E06 stands and is reflective of the emotional nature of the AC experiments conducted.

Also interesting is that the E02 experiments showed levels of reduced Anger and increased Sadness. For a cognitive experiment with little facial interaction, this is also quite reflective of the actual data captured both automatically and via the GEW self-reporting processes. The reduction in the Joy emotion across all the experiment groupings is also significant but this may have been different if a control other than the E01 group was used in the glmmTMB statistical models.

**Thesis research hypothesis revisited:** As part of this thesis and also as a focal point for the AC research and experiments conducted the following thesis hypothesis $\boldsymbol{H^0}$ was formally defined.

- $\boldsymbol{H^0}$**-** *The fusion of affective sensory data from vision analytical systems with multi-sensory physiological analytical systems does not significantly increase the sensitivity and specificity (predictive performance) of emotion recognition when tested on subjects in typical emotionally generated situations or events.*

Considering the statistical evidence presented in chapter five across the macro, micro and applied evaluations and the findings and salient conclusions discussions in this chapter and in chapter five there is significant evidence to reject the null hypothesis in favour of the alternative hypothesis $\boldsymbol{H^1}$.

The rejection of the null hypothesis $\boldsymbol{H^0}$ in favour of the alternative hypothesis $\boldsymbol{H^1}$ is based on the following main justifications.

***H*[1] justification 01:** The macro analysis supports ***H*[1]** primarily for the fusion of the EmotionViewer vision adaptor with the GSR and skin Temperature sensors in an E4 wearables adaptor.

***H*[1] justification 02:** While the micro evaluation did not confirm significant SV for the Emotion classification itself, SV was significantly confirmed across both the ExpGroup and the ExpID. This confirms that SV is certainly present at the micro individual level and perhaps deeper levels of investigation for the Emotion classification may be required in future research. The duration of experiments and perhaps the issues raised by Andreassi (LIV, SR, IR) (Andreassi, 2007) may also have been impacting factors for individuals participating in the AC experiments at the individual level.

***H*[1] justification 03:** The generalized linear mixed models evaluation and investigations provided statistical evidence of how wearable sensors (EFS, EmpaticaEmotions adaptor) can be used to increase the sensitivity and specificity (predictive performance) of Emotion recognition when fused with vision sensors (EFS, EmotionViewer adaptor).

For completeness the formal thesis research alternative hypothesis ***H*[1]** is stated below.

- ***H*[1]-** *The fusion of affective sensory data from vision analytical systems with multi-sensory physiological analytical systems **does significantly increase** the sensitivity and specificity (predictive performance) of emotion recognition when tested on subjects in typical emotionally generated situations or events.*

That concludes the overall thesis hypothesis evaluation, reporting and salient conclusions work. The remainder of this chapter, including the next section addresses the final thesis objective (TO10) in relation to the many problems, challenges, outlooks and projections for the AC field in the future.

### 6.2.3 Identified Problems and Challenges

This section consolidates a range of problems and challenges that the AC and AS fields are likely to face in the coming decade. It revisits and discusses the information fusion review paper by Poria et al. and also provides a summary audit of the problems and challenges sections presented in chapter two.

Poria et al. (Poria, Cambria, Bajpai, & Hussain, 2017) have conducted extensive AC research; their work is particularly current and exists as a fitting, validated, and complimentary reference resource to the research that has been conducted for this thesis. Their findings in relation to the superiority of the vision modality have already been highlighted and this is likely to fuel new vision based start-ups and increased innovation which will be beneficial across the AC field. In particular the ensemble approach which incorporates the best in deep learning techniques combined with the more traditional handcrafted feature extraction methods and techniques may be the way forward, particularly in relation to the multi-modality fusion frameworks.

Specifically on the topic of fusion, it is vital to state the importance of continual unimodal research advancements, as any innovations at this level will naturally lead to further advanced progression of multi-modal and sensory fusion science and technologies. Poria et al. (2017) present clear justification for the fusion of text based affective analytics, specifically with audio and visual features which shows promise for the affective management, monitoring and supervision of social media platforms.

Directly in relation to emotion generation, there is the need for 1) real-world expression, as opposed to acted expression (which has already been discussed under vision), 2) expansion into more complex emotional state processing to compliment the traditional standard set and 3) the increased necessity for subject independence as core considerations for future research (Poria, Cambria, Bajpai, & Hussain, 2017).

Subject independence is a challenging problem in AC and this should drive researchers to increasingly test their platforms and services across gender, ability profiles, age, and social and ethnic groups. Subject independence has also been a major observation and finding in the AC experiments research conducted.

The AC context of a system also needs consideration. Throughout the literature the context domains tend to be quite rigid, so in order to address this issue a focus of research into multi-contextual capability is important. With reference to the thesis research conducted, there was an applied multi-contextual tendency throughout, with the various experiments addressing a number of real-life related scenarios where affect may be generated. SenseCare is another example of research with a multi-contextual potential. While the short-term goals of the SenseCare platform is in the dementia and Alzheimer's care domains, the long term aim of the platform is for a multi-contextual focus across many eHealth application fields.

Also noted by Poria et al. (2017), [p. 119], is that the most widely used fusion method in the literature was feature level fusion but that since 2010 onwards there has been an ever increasing shift to decision-level fusion methods. Poria et al.

(2017) state that this may be due to the fact that feature-level fusion can be quite processing hungry and also requires constant evaluation and analytics on the best feature selection methods and techniques.

The interrelationship between time and emotions is also a future challenge for AC multi-sensory fusion research. Poria et al. (2017) suggest that a lot more research is required into *temporal dependency* (Poria, Cambria, Bajpai, & Hussain, 2017), [p. 119] and particularly in relation to utterances at time ***t*** versus utterances at time ***t+1***. Directly related to temporal interactions is the understanding of affect in conversation and how the emotions of one person can impact on that of another in a communication process. This future research work will involve the modelling of inter-person emotion dependency and can be expected to have a significant impact on multi-modal fusion related research in typical multi-user context scenarios.

In order to formalise the many problems and challenges that lie ahead for the AC and AS fields, a full audit/review of the summary discussion sections provided in the state of the art chapter two was conducted and has been formulated into the following two figures, Figure 6-4 AC Problems and Challenges - Part 1 and Figure 6-5 AC Problems and Challenges - Part 2.

| Problems and Challenges Analysis across SoTA Chapter - Part 1 | | | | |
|---|---|---|---|---|
| Topic area | Vision sensors | Wearables sensors | Other Modalities | Sensory Fusion |
| Image Quality | √ | | | |
| Image resolution | √ | | | |
| Image blur | √ | | | |
| Noise | √ | √ | √ | |
| Occlusion | √ | | | |
| Customisation | √ | √ | √ | √ |
| Personalisation | √ | √ | √ | √ |
| Immutability | √ | √ | √ | √ |
| Emotion set | √ | √ | | √ |
| Sensitivity and specificity | √ | √ | √ | √ |
| Cultural and ethnic | √ | | | |
| Amalgamation | √ | √ | √ | √ |
| Interoperability | √ | √ | √ | √ |
| Security | √ | √ | √ | √ |
| Ethical | √ | √ | √ | √ |
| Standards | √ | √ | √ | √ |
| Legislation | √ | √ | √ | √ |
| Pricing | √ | | | |
| Deep learning | √ | | | √ |
| Multiple arousal theory | | √ | | |
| Movement | √ | √ | √ | √ |
| Medicine (impact of drugs on emotions) | √ | √ | √ | √ |
| Sensor placement | √ | √ | √ | |

**Figure 6-4 AC Problems and Challenges - Part 1**

Both figures provide a listing of key identifiers relating to the problems and challenges that have already been discussed in the vision, wearables, other modalities and multi-sensory fusion sections of chapter two of the thesis. The order of the identifiers relate to how they were discussed in the various sections. The green tick marks indicate the specific chapter two modality section where the problem/challenge was originally discussed, while the red tick marks indicates that the specific problem/challenge may also apply to other modalities/areas that were discussed in the chapter two review sections.

| Problems and Challenges Analysis across SoTA Chapter - Part 2 | | | | |
|---|---|---|---|---|
| **Topic area** | **Vision sensors** | **Wearables sensors** | **Other Modalities** | **Sensory Fusion** |
| Health and safety | | √ | √ | |
| Moral | √ | √ | | |
| Social | √ | √ | | |
| Multi-discipline | √ | √ | √ | √ |
| Environment | | | √ | √ |
| Temporal | | | √ | √ |
| Body augmentation | √ | √ | √ | |
| Soft data | √ | √ | √ | √ |
| Hard data | √ | √ | √ | √ |
| Learning | | | | √ |
| Automated fusion | | | | √ |
| Low level AC | √ | √ | √ | √ |
| High level AC | | | | √ |
| Data imperfection | √ | √ | √ | √ |
| Outliers (Spurious data) | √ | √ | √ | √ |
| Conflicting data | √ | √ | √ | √ |
| Modality | √ | √ | √ | √ |
| Correlation | √ | √ | √ | √ |
| Alignment/Registration | √ | √ | √ | √ |
| Association | | | | √ |
| Processing framework | | | | √ |
| Operational timing | √ | √ | √ | √ |
| Static Vs Dynamic - (Fusion) | √ | √ | √ | √ |
| Dimensionality | | | | √ |

**Figure 6-5 AC Problems and Challenges - Part 2**

With reference to the two figures presented, the following is a list of some of the major problems and challenges that the science and technology of AC will face in the coming years;

- Customisation and personalisation
- Immutability
- Emotion set expansion
- Multi-sensory fusion
- Sensitivity and specificity issues
- Amalgamation
- Interoperability

- Security
- Standards (incorporating GDPR)
- Legislation
- Real-world environment domain applications
- Multi-disciplinary inputs

This section has summarised a momentous work plan of problems and challenges that AC must engineer for and address over the coming decades. In readiness and of critical importance is the fact that the AC research community is driving this agenda and it has a solid handle on the workload that needs to be carried out, but there is a caveat.

Only by aggressively incorporating a major unification approach can the work plan discussed in this section be delivered upon in the future. In addition to all of the scientific and technological developments there are critical requirements for increased efforts to reach out and integrate with the various multiple disciplines that can bring their expertise, related research and knowledge to addressing the many complexities that have been outlined. The Multidisciplinary Innovation eXchange (MIX) AI conference is one example of such an initiative that is addressing this divide (MIX-AI, 2018) and is a major and welcome advancement for AC researchers.

The foreseeable future is most definitely embedded in the multi-sensory data fusion agenda. There are many problems and challenges to overcome but the prospect of truly affective and cognitively powered computing firmly rests with its growing and innovative research community. The continual embracement and integration of the multi-faceted and multi-disciplinary nature of the field is the single most strategic factor to ensure further growth and the next phases in the evolution, development and futures of AC.

## 6.3 Affective Computing Research Outlooks and Projections

This section opens with a revisit to the application domains for AC with forward thinking, thoughts and references to likely advancements. This is then followed by an update on future scientific and technological developments relating to vision, wearables and other significant technologies. The section concludes with a focused discussion on open issues and future activities directly related to the outcomes of this thesis research.

### 6.3.1 Affective Computing Application Domains – Revisited

This section presents an update and discussion on selected current application domains for AC and where future potential exists for the technology.

**EHealth domain revisited:** The Medical Futurist Institute question if algorithms and robots should mimic empathy? In an article, they reference the World Health Organisation which has estimated a worldwide shortage of *around 4.3 million physicians, nurses, and allied health workers* (The Medical Futurist Institute, 2018). At the same time there are major global increases in dementia, Alzheimer's, obesity, and diabetes. The institute also discusses how illnesses are spreading quicker and are easier to catch and also reference the major ageing global population. These evolving global factors could lead to the formulating of a medical perfect storm and could well be the drivers behind future *medical virtual assistants, healthcare chatbots or humanoid robots* according to the Medical Futurist Institute (The Medical Futurist Institute, 2018). The Medical Futurist article cites a number of advances in affective medical technology, SoftBank[20], BabyX[21] virtual baby project, MPathic-VR[22] emotive virtual humans, and We Are Alfred[23] which is a technology to solve the emotional disconnect between young doctors and elderly patients.

The Connected Health Symposium in Boston (Wicklund, 2016) held a special session on technology that can measure mood and help doctors to monitor and tailor their therapies. The session with invited technology innovators discussed potential applications in affective health. Wicklund (2016) explains that affective applications in healthcare are still quite new but that they are attracting attention. He explains how affective computing may be used by therapists and mental health providers to detect *emotions in patients who might not realize or want to convey what they're feeling* (Wicklund, 2016). Pediatricians could use AC systems in their *work with children with autism or ADHD. Doctors could use the technology to help patients dealing with stress, depression, substance abuse issues, even sleep management. And the pharmaceutical industry might use it to study how patients react to a certain medication or medication therapy* (Wicklund, 2016).

O'Connell discusses loneliness which she describes as the *sadness that comes from lacking friends or company* and a *silent assassin that wreaks havoc on people's lives* (O'Connell, 2017), [p. 1]. The article explains that there is increasing research evidence linking loneliness to *dementia, depression and accidents, disrupted sleep patterns, altered immune systems, higher levels of stress hormones, and inflammation* (O'Connell, 2017), [p. 1]. O'Connell

[20]https://singularityhub.com/2017/08/29/japans-softbank-is-investing-billions-in-the-technological-future/#sm.00137vsd7197weccts61xqxnb1ouh
[21] https://www.bloomberg.com/news/features/2017-09-07/this-startup-is-making-virtual-people-who-look-and-act-impossibly-real
[22] https://www.trendhunter.com/trends/mpathic-vr
[23] https://www.youtube.com/watch?v=pOW7oG6bIFI

references research that links isolation with increasing the risk of heart disease and stroke by about a third and a study in the journal Cancer which found that *socially isolated women had a 40 per cent higher risk of recurrence of breast cancer and a 60 per cent higher risk of dying* (O'Connell, 2017), [p. 1]. One of the most striking findings in this article is the work of Professor Rose Anne Kenny at Trinity College Dublin. Kenny explains that *prolonged lack of social engagement can actually trigger a chronic background inflammation* in a person's body which could cause heart disease; neurodegenerative diseases; colonic carcinomas and other cancers (O'Connell, 2017), [p. 2].

Sadness evolving from prolonged loneliness can lead to deep depression. The Carnegie Mellon University, Robotics Institute is conducting research into depression assessment. Their research project uses automated facial image analysis that extracts the *type and timing of nonverbal indicators of depression* (Carnegie Mellon University, 2018), [p. 1]. The technology uses facial expression, head motion and gaze in their classification algorithms. The institute envisions the integration of their technology as a compliment to existing methods of depression assessment in the future. Girard and Cohn have also conducted research relating to depression analysis. They believe that new audio-visual based measurement of behaviour have the potential to *improve screening and diagnosis, identify new behavioural indicators of depression, measure response to clinical intervention, and test clinical theories about underlying mechanisms* (Girard & Cohn, 2015), [p. 75].

Mertz from IEEE Pulse interviewed Professor Picard and asked about her work in relation to depression and her hopes for the future (Mertz, 2016). Picard points out that in the current medical system, depression is not formally identified and acted upon until a diagnosis is given by a medical practitioner. She argues for data science and AC based techniques that can *show people that certain daily choices they make increase or decrease their risk of becoming depressed* (Mertz, 2016). Such a system which she describes as an emotional weather forecast (not perfect) *can learn how to forecast which measures make depression more likely to happen* in a person (Mertz, 2016). Such an AC powered depression analytical system can assist a person in preparing for a possible storm or better still provide a *chance to change the weather - to change the health outcome* (Mertz, 2016).

Picard believes that society *may be able to prevent a lot of depression by observing behavioural changes in an individual patient early (on) and then nudging them in ways that can head off disease* (Mertz, 2016). The potential exists for such technology to act like an early warning system before the depression takes over and the condition produces total incapacitation for an individual.

**Other domains revisited:** Research into touch induced emotional stimulation by Cabibihan and Chauhan (2017) presents a tele-touch device that communicates touch via vibration, warmth and tickle over the Internet using haptic devices (Cabibihan & Chauhan, 2017). Their work involved three groups, one which involved human-to-human touch, another used the tele-touch systems and a third was a control group. While monitoring for changes in HR and GSR they found that the HR of the subjects were not significantly different between the tele-touch group and the group with human-to-human touch (touch by loved ones) and were in direct contrast to the control group where no touch stimulation was provided. Their GSR results (Cabibihan & Chauhan, 2017), [p. 115], demonstrated that all three touch conditions were different from each other.

Affectiva is deploying its platform with partners and in 2016 entered the gaming market to *enable emotion-aware games and robust game analytics in an accessible and scalable manner* (Affectiva, 2016). When integrated into games platforms, the Affdex SDK provides for the modification of player interactions and games dynamically. Affectiva discuss how emotions can be used to alter the game plan or used as control mechanisms by a player. Emotions analytics can also be used to manage frustration levels and to increase or decrease complexity of the game for the user. According to Affectiva, AC integration into games platforms can also provide back-end data analytics, emotion data for usability and marketing purposes, and emotion analytics on players and eSport/gaming audiences in real-time.

The AC application domains are certainly on a learning curve at present and no doubt pitfalls should be expected in the future. That said, it is the belief that the science and technology is now at an early stage and perhaps very similar to when the first graphical user interface (GUI) based operating systems entered the marketplace. Such early GUI systems had quite basic functionality but with both hardware and software advances over time they became highly sophisticated and changed the world of computing.

Perhaps new and innovative AC application domains may follow a similar trajectory, but a word of caution is relevant. AC is a highly complex problem at the very heart and soul of the human psyche and with this in mind, any future advances must be firmly driven with human centric engineering in mind. On this cautionary note, the next section delves into some of the future scientific and technological challenges facing the AC field.

### 6.3.2 Future Scientific and Technological Challenges

This section presents scientific and technological developments on the horizon that AC researchers should be aware of. It also highlights and discusses the potential dangers, threats and challenges to be faced for AC and AI in the future.

**AC and vision sensors:** Ultra-wide band (UWB) (Mitchell, 2017) is a conventional radio communications technology investigated by Vokorokos et al. (Vokorokos, Mihaľov, & Leščišin, 2016) in relation to its potential for integration with depth camera technologies. According to Vokorokos et al. (2017) UWB sensors can penetrate through walls and can also detect movement of a human body in a space. UWB can also detect movement within the body itself and has the potential to provide non-invasive sensing capabilities of vital parameters of the human body to eHealth monitoring and tracking systems (incorporating AC systems).

Their research proposes the integration possibilities of UWB with depth cameras. In a typical scenario where a depth camera faces occlusion, the UWB sensors may be able to supply supporting data on the face or body of a subject. Such UWB sensor developments and integration with depth camera hardware and software offers future possibilities in addressing some of the know AC limitations of vision sensor technologies.

In 2018, Intel launched Real Sense SDK 2.0. which is now available as open source and with cross platform editions (Intel, 2018). The SDK platform comes with two new depth camera offerings. The D415 and D435 (designed for virtual reality) depth cameras use the Intel Real Sense vision processor D4, both have a maximum range of 10 meters and support indoor and outdoor applications (Intel, 2018). While Intel has tended to re-focus efforts on generic vision technologies, the open source and cross platform nature of the new Real Sense SDK is significant and provides core technologies for developers working on advanced AC vision related solutions in the future.

**AC and wearable sensors:** Wearable technologies could be used to assist with the understanding of how a conversation is going. Barrett (2017) explains how researchers at MIT have created a wearable system that can advise *whether the person you're talking to is happy or sad* (Barrett, 2017). The system uses physiological signal data combined with audio tone, pitch, energy, and word choice. While this is a very early stage system, the MIT researchers, Ghassemi and Alhanai point out the current limitations (overall tone 83% accuracy) but predict the future potential for their systems to incorporate not only happy or sad but to also offer alerts for boredom, tension, and excitement. Such a system has opportunities in emotional intelligence applications and also offers the potential for deep personalisation relating to both the user and the subjects they interact with.

The form factor for wearable devices is changing. Lightbody (2016) reports on stretchable electronic patches that measure electrical activity in the heart, brain and muscles such as the device developed by the Rogers Research Group at the University of Illinois (Lightbody, 2016). John Rogers and his colleagues are credited with discovering a stretchable form of silicon that can be used in the creation of ultramalleable devices (Lightbody, 2016) such as that represented in Figure 6-6 Rogers Research Group - Epidermal Electronics.

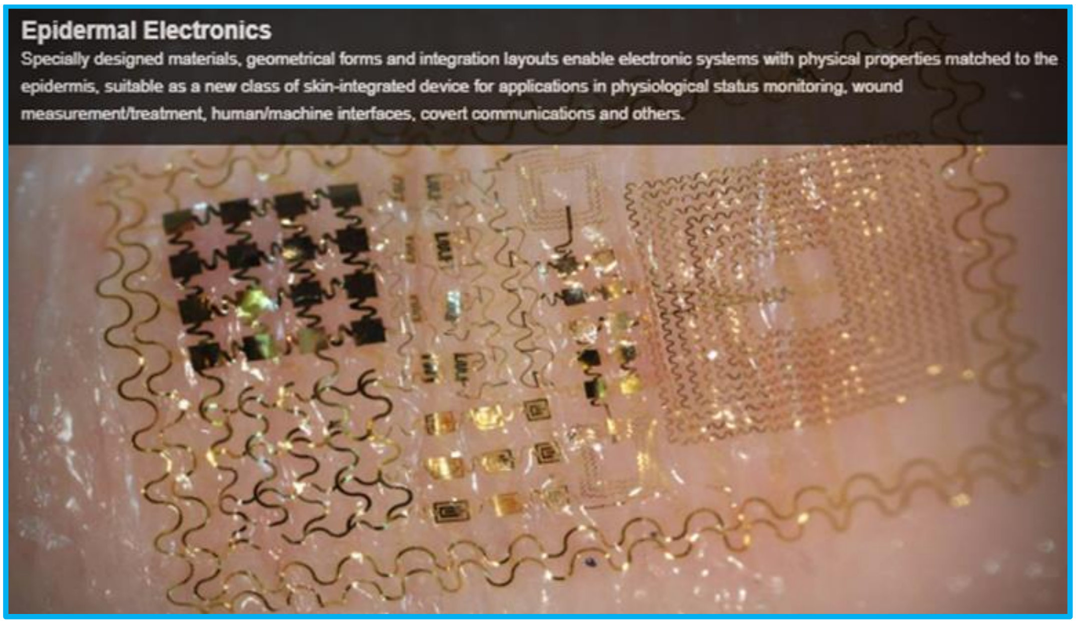



**Figure 6-6 Rogers Research Group - Epidermal Electronics (Rogers Research Group, 2018)**

Rogers believes that such ultramalleable sensors are the future and possibly the direction where wearables are likely to go next. According to their Internet site, their research seeks to *understand and exploit interesting characteristics of 'soft' materials, such as polymers, liquid crystals, and biological tissues as well as hybrid combinations of them with unusual classes of micro/nanomaterials, in the form of ribbons, wires, membranes, tubes or related* (Rogers Research Group, 2018). Rogers and his group have conducted numerous projects in materials electronics.

Another relevant project is their Skin-Like Microfluidic Systems for Capture, Storage and Chemical Analysis of Sweat (Rogers Research Group, 2018) which is shown in Figure 6-7 Rogers Research Group (Sweat Analytics Patch) This is a soft, flexible and stretchable patch type device that can deliver data wirelessly for quantification in relation to the analysis of sweat. Clearly such a flexible wearable device has major potential for future AC research and applications.


**Figure 6-7 Rogers Research Group (Sweat Analytics Patch) (Rogers Research Group, 2018)**

Patch size, flexible wearable sensors are likely to be in the distant future but smart clothing as discussed previously is certainly advancing, with many opportunities for the AC field. Sawh (2017) has produced a recent review[24] across a range of smart clothing products and providers in the marketplace. The below is a series of extracts from this review that are of interest from an AC research perspective (Sawh, 2017).

- Polar Team Pro Shirt monitors heart rate and movement data and can also stream live data.
- Komodo Technologies launched the compression sleeve that uses electrocardiogram (ECG) technology to monitor heart rate activity. It also has sensors on board to monitor body temperature, air quality and UV rays.
- Levi's Commuter Trucker Jacket will be the first piece of connected clothing to launch from Google's Project Jacquard platform (Google,

[24] https://www.wareable.com/smart-clothing/best-smart-clothing

2018). The jacket has built in touch and gesture sensitive areas on the jacket sleeve.

- Neopenda's monitor is fitted inside a hat for new born babies. It measures temperature, heart rate, respiratory rate and blood oxygen saturation. Up to 24 baby hats can be wirelessly synchronised for data monitoring and analytical purposes.

**Micro Mote ($M^3$):** The Michigan Micro Mote ($M^3$) claims to be the world's smallest computer with measurement of less than a centimeter. The $M^3$ is a functioning autonomous computing system that can act as a smart sensing system. Prof Blaauw (2018) explains that similar to traditional computing, the $M^3$ sensors are used for the input and radio communication is used for output. The $M^3$ also has a power supply that is charged via on-board solar cells (University of Michigan, 2018).

Advancements in IoTs are increasingly demanding that computing provides power in a miniature form factor. In the video demonstration[25] the lead researchers explain how the $M^3$ can sense pressure, temperature and that it also has image processing capabilities. One of the potential applications discussed is how the $M^3$ could be used in future medical diagnosis with the device processing and sending images directly from within the human body. Devices like the $M^3$ open up numerous opportunities for AC research to use such devices in their original form factor or to integrate them into customised AC sensors.

**Neuro-Sensitive Foam:** Swiss biosignalling developer MindMaze have created a foam based insert for virtual reality headsets called MASK. Foam based

25 https://www.eecs.umich.edu/eecs/about/articles/2015/Worlds-Smallest-Computer-Michigan-Micro-Mote.html

electrodes can measure electrical signals in the skin and are able to *mimic users' expressions on their in-game avatars before they've actually formed that smile or frown in real life* (Burns, 2017). According to MindMaze founder Tej Tadi, MASK has potential applications in autism research and related products and could also be *helpful for aphasia* (Lava, 2016) *patients who've suffered a loss in their ability to understand and communicate through speech, as following a stroke* (Burns, 2017). MASK is an interesting technology, founded on electromyography science and is included in this section to highlight novel approaches in AC related research and is an indication of what is yet to come regarding sensory interface engineering and the challenges it faces in real-world applications.

**AC and neural computing:** It has been reported that Facebook is researching ways to control computers directly by human thought processes, at its 2017 annual developer's conference (RTE, 2017). Business Insider also reports possible brain related investigation projects at Facebook's Building 8 research centre. Heath (2017) quotes Zuckerberg's belief in the potential of being able to send *full rich thoughts to each other directly using technology* (Heath, 2017).

Glaser (2017) reports on Neuralink[26] which is a new company, set up by Elon Musk to develop ultra-high bandwidth brain-machine interfaces to connect humans and computers (Glaser, 2017). Glaser explains that Musk sees Neuralink as a digital layer located above the cortex that is built into the brain with the capabilities of directly linking the human brain. Musk believes that this implant/interface technology could *help humans keep pace with rapidly changing*

[26] https://neuralink.com/

*accelerating advancements in AI* (Glaser, 2017) so that humans may not be left behind.

Regardless if any of these technologies come to fruition over the next decade, the brain is the new frontier and the above is evidence of the scientific and technological challenges that need to be tackled in the pursuit of future advancements in relation to AC.

**AC and AI dangers, threats and challenges:** As a lead into this discussion, some recent comments by Gartner on Emotion AI are relevant. Zimmermann, vice president at Gartner, predicts that *by 2022, your personal device will know more about your emotional state than your own family* (Goasduff, 2018) . Gartner believe that 2018 will see ever increasing demand and application for Emotion AI (AC). This section considers the possible dangers, threats, challenges, and societal implications for AC and its AI parent. It addresses some of the issues and challenges that governments, society and organisations need to consider with regards to the future of cognitive based technologies.

In relation to the future of AI (incorporating AC/Emotion AI), advances in deep learning technologies and algorithms will open up cognitive applications to many new and fascinating domains. Rozenfeld (2016) explains how a blind software developer at a recent Microsoft conference was able to understand the content of a live scene in front of them by taking a snapshot, and having an AI system explain the scene in real-time. The system could also describe facial expressions of images in the scene. Rozenfeld (2016) believes that future AI *intelligent machines will be able to pick up subtle cues, such as differentiating fake smiles from real-ones* (Rozenfeld, 2016) and that it will also be able to predict a person's needs in the form of intelligent personalised assistance, which is already advancing today at a rapid pace.

Under the Obama led US government, a series of workshops were set up in relation to preparing for the future of AI. Announced by Ed Felten in 2016, the series of workshops were around the themes of legal and governance, AI for social good, safety and control for AI, and social and economic implications for AI technologies in the near-term (Felten, 2016). This forward thinking initiative of addressing and preparing for the future of AI is in stark contrast to the thinking of the current Trump led US government. Webb from the Los Angeles Times quotes treasury secretary Steven Mnuchin in relation to the futures of AI as saying that *significant workforce disruption due to AI is 50 to 100 years away* (Webb, 2017). Mnuchin said he was personally not worried *about robots displacing humans in the near future* (Webb, 2017).

Regardless of these conflicting US government opinions, AI and its future has dominated news and media over the last twelve to eighteen months. One organisation preparing and taking AI seriously is The Future of Life Organisation (The Future of Life Institute, 2018). This organisation has a highly significant list of founders, scientific advisors and followers. They have produced a set of twenty three AI principals of which a number are directly relevant to AC. The following extracts from the AI principles reproduced below indicate concerns, challenges and issues from an AC/AI futures perspective.

- **Judicial Transparency:** Any involvement by an autonomous system in judicial decision-making should provide a satisfactory explanation auditable by a competent human authority.

- **Responsibility:** Designers and builders of advanced AI systems are stakeholders in the moral implications of their use, misuse, and actions, with a responsibility and opportunity to shape those implications.
- **Personal Privacy:** People should have the right to access, manage and control the data they generate, given AI systems' power to analyse and utilize that data.
- **Race Avoidance:** Teams developing AI systems should actively cooperate to avoid corner-cutting on safety standards.
- **AI Arms Race:** An arms race in lethal autonomous weapons should be avoided. (The Future of Life Institute, 2018)

On a more practical level, and with reference to the GDPR (EU, 2018) there are ever increasing demands for explanation of the reasoning capabilities of AI systems. With reference to such transparency, Jaakkola of MIT sees the need for (AI) models to be able to verify their processing in the form of how predictions are made (Hardesty, 2016). Jaakkola believes that humans should also have an element of control over these models and should be able to *exert some influence in terms of the types of predictions* (Hardesty, 2016) they make.

Opening up these AI black boxes (models) is also on the agenda of the financial world. Knight (2017) reports and references the GDPR in relation to algorithmic accountability and also believes that companies in the future will have to explain decisions made by AI algorithms (Knight, 2017). Knight advises that the Defense Advanced Research Projects Agency (DARPA) in the US is taking this issue of AI explanation and transparency very seriously and are currently funding thirteen projects around the theme of making autonomous machines explain themselves (Knight, 2017).

Finally and in conclusion to this section, the original thoughts of Picard when the conceptualisation of AC was still at a very early stage are now extremely relevant (Picard, 1997). In chapter four, addressing AC potential concerns, it is right and fitting to highlight her commentary that is increasingly more relevant today.

The following extracts identify specific thoughts and concerns that Picard had at the time of her original writing in 1997:

- With reference to the recent economic surge is AC commercial companies today, at the time Picard wrote that *poorly timed or overdone affect will be worse than no affect* (Picard, 1997), [p. 118].
- In relation to privacy, Picard believes that affective information must be treated with *respect and courtesy, and its privacy preserved according to the desires of the humans* (Picard, 1997), [p. 118] being monitored by AC platforms.
- In a section on accuracy, Picard discusses the use of the polygraph in early times and raises a concern for the future in relation to what can be *recognised in you against your will* (Picard, 1997), [p. 119]. On highlighting this issue, Picard could not have predicted that such covert tracking is actually possible today and perhaps happening already to citizens worldwide.
- Picard points out that even if computers are unbiased by emotion they are still *biased by their programmers, and by what they have learned* (Picard, 1997), [p. 122]. With this in mind, Picard writes that *computers are not purely objective* (Picard, 1997), [p. 122], and today in the case of AC there may be hidden agendas in place.

Under symmetry in communication, Picard (1997) indirectly refers to the GDPR. At the time of writing her book, she was advising that AC systems should have the ability to provide explanation and reasoning in relation to the emotion analytics they perform on an individual. Picard (1997) quotes the three laws of robotics from The Bicentennial Man (Asimov, 1976) and applies them in an AC context (Picard, 1997), [p. 129]. These laws relate to controlling injury to humans, ensuring that computers are controlled by humans and providing for the computing entity itself to protect its own existence. Two decades ago, these laws may not have seemed realistic, but with the rapid pace of AI there is certainly justification for their deep consideration and application today. Most of what Picard (1997) wrote may have seemed to be in the realms of science fiction at the time but today the points made are extremely significant for AC and AI research.

In summary of this discussion on the dangers, threats and challenges of AI and AC, it is fitting to quote the last paragraph of chapter four from Affective Computing. Picard writes that *the human-centered goal of affective computing needs to be practiced throughout its development: making machines better able to serve people by giving them the affective abilities that contribute to this goal* (Picard, 1997), [p.137].

It remains to be seen if AC holds to the original aspirations of Picard, that it stands the test of time in terms of human centricity, and that its embedded AI technology is not exploited in many precarious ways in future times, yet to come.

### 6.3.3 Thesis Open Issues and Future Related Research

This section narrows down the focus to exclusively discuss open issues and future considerations concerning the research conducted for this thesis. These are discussed below under a number of related headings.

**Conceptual architecture open issues and future related research:** The conceptual architecture research has been the foundation of the EFS prototypical solution developed. The S-Strata and AC-Strata stratification models are open for future investigation and research. This may incorporate applied work relating to semantic reasoning, ontologies and addressing the environmental problems and challenges real-world AC related data fusion brings about. At a conceptual level, more research is required into the expansion of AC emotion classification possibilities and the complexities that personalisation will introduce from an architectural perspective.

**EFS open issues and future related research:** The EFS is currently a prototypical set of software artifacts developed as a result of the thesis research. While the EFS has been used extensively with both the vision and wearables adaptors it has also been tested in the SIGMA facility for extended duration running all four sensor adaptors that were discussed in chapter four. The EFS needs to have additional adaptors engineered and developed, both open source and proprietary. Some of this work has already started with the likes of the Affectiva SDK technologies.

Expansion of the EFS platform into a multi-user cloud and mobile based solution also needs to be investigated. Some of this is actually underway at present as part of SenseCare and other SIGMA related research being conducted. Classification algorithms need to be identified for wearable adaptors and for any other new sensor adaptors to be developed for the EFS. This will involve the integration of statistical and machine learning algorithms that can be easily facilitated and incorporated into the EFS architecture. The EFS platform can also be re-engineered at the server end to incorporate statistical and machine learning mechanisms that implement feature, decision or hybrid fusion methods and techniques.

**Thesis experiments open issues and future related research:** The experiments that were conducted were extremely time consuming and it is here a number of improvements could be made for future AC researchers. The paper based GEW form completed after each experiment is extremely effective. It is spontaneous, fast and covers personal thought processes and has a strong foundation in psychology. That said, it needs to be investigated if it can be easily automated and if such a system would provide better results overall. Such an automated GEW would considerably reduce administration efforts, provide more accurate data transfers and create automatic self-reporting datasets.

In the experiments that were conducted, the sensors compiled the data for a group of experiments. Once the group dataset was compiled for a participant there was the requirement to extract the data for each experiment based on recorded time slices. Again this is an extremely tedious task that requires automation investigation. Researcher Robin Spiteri studying data science at CIT has started to investigate and build a data extractor system that will address this issue and other data manipulation problems. In the future, such data extractor software resources should be available for more productive manipulation of the EFS datasets.

One other area that requires future investigation is into how the EFS and sensor adaptors could be taken out of a laboratory setting and deployed into an everyday real-world environment. This is a highly recommended focus for EFS related future research resulting from this thesis.

**Statistical reporting open issues and future related research:** The datasets produced from the EFS experiments have been primarily used to address the thesis hypothesis. The datasets have also got other possibilities and could be used in a number of the following scenarios:

- GEW statistical analysis was conducted primarily in relation to the validation of the EmotionViewer Emotion classification. The GEW dataset could be investigated further using the individual E4 sensor responses. This in itself is a highly significant additional research opportunity and could also intensely research physiological sensor relationships across the experiment groups and the individual experiments in conjunction with the GEW results.
- The datasets captured using the wearables adaptor can also be used for the development and testing of emotion classification from physiological signals. Opportunities also exist to research and compare the EFS generated dataset with other established physiological datasets available at repositories such as PhysioNet (National Institute of General Medical Sciences, 2017).
- Using the raw E4 sensor data streams it will be possible to develop time line based statistical analysis. For example, for a number of seconds of E4 sensor data from the GSR sensor, the time line statistical analytics could demonstrate the transition of the GSR over short or longer time

periods. This would give valuable insights into how an emotional state can change over time and how the E4 sensor values relate.

- As discussed in the thesis findings and salient conclusions sections there are research opportunities to investigate the HR sensor in further detail and the underlying theoretical aspects of Anger, Joy and Disgust with reference to skin temperature.
- The glmmTMB mixed effect modelling could also be investigated with changes to the control group (E01), changes in the model parameters (ExpGroup, ExpID and ID) and alternative stepwise reduction approaches.

**Other open issues and future related research:** As already discussed under the thesis contributions section, this research will live on and evolve in the form of related AC research. SenseCare is a live example of this evolution that is already well underway. Researchers at SIGMA are conducting AC related research that could also compliment and advance this thesis research in the future.

For example, SIGMA PhD researcher and computer scientist Michael Healy is developing vision sensory and machine learning technologies to automatically provide emotional and cognitive insights into well-being of persons suffering from dementia and related cognitive impairments. Healy's work has independent applications in eHealth while also having potential to be integrated with the EFS at both the sensory adaptor and server data fusion levels.

Another SIGMA PhD researcher with a master's specialisation in psychology is Ryan Donovan. Donovan is investigating the expansion of affective computing capabilities in capturing short-term emotional and cognitive states into detecting underlying personality traits. This is aimed at developing affective computing software that can respond more effectively to the wide variety of individual differences between people. Donovan's research is addressing one of the problems and challenges well discussed in relation to AC and involves the issue of personalisation in AC platforms. His research has application to the stratification models, the AC conceptual architecture, expansion possibilities for the AC emotion set and also to the development of personalisation capabilities in the EFS platform.

That concludes the section on AC outlooks and projections. The next and final section of chapter six provides an overall executive summary of the thesis research document, volume 1 of 2 for the reader.

## 6.4 Final Overall Thesis Research Executive Summary

At selected sections in the thesis research document, various summaries have been positioned for the reader. This section aims to provide a concise overall executive summary across all of the six chapters that have been presented throughout this thesis document, volume 1 of 2.

The thesis research motivations and objectives were presented in chapter one. This chapter provided valuable background to the motivations, direction and justification of the research. It introduced a range of problems and challenges that AC is facing. This led to a number of key research questions to be addressed for the thesis research. The formal thesis hypothesis was defined for the reader with a full set of thesis deliverable objectives. The methodology that was used in conducting the research was also introduced and discussed in this chapter.

Chapter two provided a scientific and technological literature review of the AC field. This work was conducted in the early stages of the research and acted as foundation for further research yet to come. The chapter aimed to cover both scientific and technological aspects and investigated the role of psychology in AC, vision, wearables, and other sensor modalities used in AC research. The highly related field of data fusion was also investigated with a focus on multi-sensory fusion. Chapter two additionally presented a number of AC related research projects that have been conducted and that were inter-related with the thesis research.

The conceptual modelling and design chapter three presented the research that originated as a result of the state of the art research work that was conducted. The chapter presented applied uses cases in an eHealth context along with a set of the functional and non-functional requirements of a proposed AC conceptual platform. The multi-media stratification model was applied in an AC context which led to the development of the proposed S-Strata and AC-Strata stratification models. Both vision and wearable sensor data streams were then presented as a lead in for future sensor detailed discussions in chapter four. The AC stratification models were further developed and discussed in chapter three and were applied in the context of a generic sensor adaptor and an overall conceptual architecture of a prototypical AC platform.

The EFS prototypical solution was presented and discussed in chapter four. The server components and their relationship to the overall conceptual architecture were explained. Process flow diagrams and discussions in relation to the underlying software artifacts were also provided. Both vision and wearables were the main adaptors integrated with the EFS for the AC experiments and were discussed in detail. Two other adaptors (PC inputs and BCI) at the prototype stages were also included along with technologies from Affectiva and Microsoft that were investigated as potential EFS adaptors. The chapter concluded with a detailed review of future potential and requirements for the EFS prototypical AC platform.

The AC experiments conducted and the evaluation stages relating to the thesis hypothesis were provided in chapter five. This chapter introduced the experiments and detailed the overall design and organisation relating to the conducting of the experiments. The various datasets generated as a result of the experiments were presented and explained for the reader. The statistical reporting and analysis provided investigations at both a macro and micro level across the experiment datasets. Applied investigations were also carried out and were documented in a dedicated section on generalized linear mixed effects models (glmmTMB). Using the glmmTMB R software package, investigations were carried out into the Emotion classifications of Joy, Disgust, Sadness and Anger using the Contempt emotion as a control/baseline in the mixed effects modelling approach. Chapter five concluded with summary findings and conclusions at the macro, micro and applied levels of investigation.

This final chapter six provided details of overall thesis research contributions, high-level salient conclusions connected to the hypothesis evaluations and a decision in relation to the acceptance or rejection of the formal thesis hypothesis. The chapter also provided futuristic evidence on outlooks and projections for the AC field and also addressed the final thesis objective TO10, which was to conduct research into the future problems, challenges, and directions of the AC field.

In final and absolute conclusion, **thank you sincerely** for your time in reading and working through this PhD research journey and its many related efforts that have been documented in this thesis volume 1 of 2 and in the associated appendices to the thesis in volume 2 of 2.

# 7 References

AAAC. (2004, January 01). *Network of Excellence HUMAINE*. Retrieved April 14, 2017, from AAAC: http://emotion-research.net/projects/humaine/aboutHUMAINE

AAAC. (2015, June 25). *AAAC Toolbox*. Retrieved April 14, 2017, from http://emotion-research.net/toolbox

Adolphs, R. (2010). Emotion. *Current Biology, 20*(13), 549 - 552. Retrieved February 22, 2018, from http://www.cell.com/current-biology/abstract/S0960-9822(10)00649-4?_returnURL=http%3A%2F%2Flinkinghub.elsevier.com%2Fretrieve%2Fpii%2FS0960982210006494%3Fshowall%3Dtrue

Advanced Brain Monitoring, Inc. (2017). *Advanced Brain Monitoring.* Retrieved March 15, 2017, from http://www.advancedbrainmonitoring.com/

Affectiva. (2016, March 01). *Affectiva enters gaming market with its emotion AI technology to deliver on promise of emotion-aware games*. Retrieved January 24, 2018, from PR NewsWire: https://www.prnewswire.com/news-releases/affectiva-enters-gaming-market-with-its-emotion-ai-technology-to-deliver-on-promise-of-emotion-aware-games-300228640.html

Affectiva. (2017). *Affdex - Uncover the emotional power of your advertisements and media content*. Retrieved January 25, 2017, from http://www.affectiva.com/solutions/affdex/

Affectiva. (2017, January 20). *Affdex SDK for iOS - SDK Developer Guide Release 3.0*. Retrieved January 25, 2017, from http://developer.affectiva.com/v3/ios/

Affectiva. (2017). *Affectiva - About Us*. Retrieved January 25, 2017, from http://www.affectiva.com/company/about-us/

Affectiva. (2017). *Affectiva Developer Portal - On Privacy*. Retrieved January 27, 2017, from http://developer.affectiva.com/privacy/

Affectiva. (2017). *Facial Expression Dataset (AM - FED)*. Retrieved January 25, 2017, from http://www.affectiva.com/facial-expression-dataset/

ALICE AI Foundation. (2017). *AIML: Artificial Intelligence Markup Language*. Retrieved January 11, 2017, from http://www.alicebot.org/aiml.html

Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. *Physiological Measurement, 28*(3), 1 - 39.

Alzheimer Europe. (2009, October 27). *Cost of illness and burden of dementia - The base option*. (Alzheimer Europe) Retrieved February 17, 2017, from http://www.alzheimer-europe.org/Research/European-Collaboration-on-Dementia/Cost-of-dementia/Cost-of-illness-and-burden-of-dementia

Amazon. (2017). *Amazon AI - Bringing powerful artificial intelligence to all developers*. (Amazon) Retrieved January 25, 2017, from https://aws.amazon.com/amazon-ai/

Amazon. (2017). *Amazon Rekognition*. Retrieved January 25, 2017, from https://aws.amazon.com/rekognition/

Amazon. (2017). *Amazon Rekognition FAQs*. Retrieved January 25, 2017, from https://aws.amazon.com/rekognition/faqs/

Andreassi, L. (2007). Human Behaviour and Physiological Response. Taylor & Francis.

Apple Inc. (2017, June 21). *Your heart rate. What it means, and where on Apple Watch you'll find it.* Retrieved September 07, 2017, from https://support.apple.com/en-us/HT204666

Asimov, I. (1976). *The Bicentennial Man and Other Stories.* Garden City, NY: Doubleday Science Fiction.

Asperges, R., Dell'Aquila, E., Di Ferdinando, A., Friedrich, R., Keary, A., Lean, J., . . . Walsh, P. (2014). *S-Cube Project (S3 ): Training Soft Skills In Social Enterprises Using Virtual Environments for Role Play.* (D. O'Byrne, & J. Lean, Eds.) Plymouth [e-book].: University of Plymouth Press.

Asthana, A., & Zafeiriou, S. (2017, May 08). *Chehra Facial Vision*. Retrieved May 08, 2017, from https://sites.google.com/site/chehrahome/home

Asthana, A., Zafeiriou, S., Cheng, S., & Pantic, M. (2014). Incremental face alignment in the wild. In IEEE (Ed.), *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, (pp. 1859 - 1866).

audEERING. (2017). *About openSMILE*. Retrieved February 07, 2017, from http://audeering.com/technology/sensai/#sensai-emotion

audEERING. (2017). *Applications - Audiary*. Retrieved February 07, 2017, from http://audeering.com/applications/

Aung, M. S., Kaltwang, S., Romera -Paredes, B., Martinez, B., Singh, A., Cella, M., & et al. (2016). The Automatic Detection of Chronic Pain-Related Expression: Requirements, Challenges and the Multimodal EmoPain Dataset. *Transactions on Affective Computing, 7*(4), 435 - 451. doi:10.1109/TAFFC.2015.2462830

AusMedtech 2016. (2016). AusMedtech 2016: Australia's Medtech conference. *Australasian Biotechnology, 26*(2), 16 - 19. Retrieved February 17, 2017, from http://pt4wp4eq4h.search.serialssolutions.com/?ctx_ver=Z39.88-2004&ctx_enc=info%3Aofi%2Fenc%3AUTF-8&rfr_id=info%3Asid%2Fsummon.serialssolutions.com&rft_val_fmt=info%3Aofi%2Ffmt%3Akev%3Amtx%3Ajournal&rft.genre=article&rft.atitle=AusMedtech+2016%3A+Australi

Averill, J. R. (1980). A Constructivist View of Emotion. In *Emotion: Theory, Research and Experience* (pp. 305-339). Academic Press.

Banafa, A. (2016, June 06). *What is Affective Computing?* Retrieved January 10, 2017, from https://www.bbvaopenmind.com/en/what-is-affective-computing/

Bao, W., Li, Y., & Gu, M. (2014). Building a Chinese Natural Emotional Audio-Visual Database. *2014 12th International Conference on Signal Processing (ICSP)*, (pp. 583 - 587). Hangzhou.

Barrett, B. (2017, January 01). *MIT Made a Wearable That Knows How a Conversation's Going.* Retrieved February 01, 2018, from Wired: https://www.wired.com/2017/02/mit-made-wearable-knows-conversations-going/

Baveye, Y., Dellandrea, E., Chamaret, C., & Chen, L. (2015, January 27). LIRIS-ACCEDE: A Video Database for Affective Content Analysis. *IEEE Transactions on Affective Computing, 6*(1), 43 - 55. doi:10.1109/TAFFC.2015.2396531

Bertot, J. C., Jaeger, P. T., & Hansen, D. (2012). The impact of polices on government social media usage: Issues, challenges,. *Government Information Quarterly 29 (2012) 30–40, 29*, 30 - 40.

Bezdek, J. C., Keller, J. M., Krishnapuram, R., & Pal, N. R. (1999). *Fuzzy models and algorithms for pattern recognition and image processing.* Kluwer Academic Publishers. Retrieved 06 05, 2018, from https://books.google.ie/books?hl=en&lr=&id=3-ubOzjjneUC&oi=fnd&pg=PR11&dq=Fuzzy+models+and+algorithms+for+pattern+recognition+and+image+processing&ots=MBEfKcnOmb&sig=1SGIRByDehIu2N1uldouZC1gvKk&redir_esc=y#v=onepage&q=%22fusion%20of%20classifiers%22&f=fal

BIOPAC. (2017). *Bioharness & Team - Physiology on a strap*. Retrieved February 01, 2017, from https://www.biopac.com/product-category/research/telemetry-and-data-logging/

BIOPAC. (2017). *Bionomadix Wireless Wearable Physiology*. Retrieved February 01, 2017, from https://www.biopac.com/product-category/research/bionomadix-wireless-physiology/

BIOPAC. (2017). *Team System 1 Person*. Retrieved April 07, 2017, from https://www.biopac.com/product/team-site-licenses/

BIOPAC Systems Inc. (2017, March 11). *MP160 Data Acquisition Systems*. Retrieved March 11, 2017, from https://www.biopac.com/product/mp150-data-acquisition-systems/

BIOPAC Systems Inc. (2017, March 11). *AcqKnowledge Software*. Retrieved March 11, 2017, from https://www.biopac.com/product/acqknowledge-software/

Blaiech , H., Neji, M., Wali, A., & Alimi, A. M. (2013). Emotion Recognition by Analysis of EEG Signals. In IEEE (Ed.), *13th International Conference on Hybrid Intelligent Systems (HIS)* (pp. 312 - 318). Tunisia: IEEE.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003, January). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 933 - 1022. Retrieved July 29, 2015, from http://machinelearning.wustl.edu/mlpapers/paper_files/BleiNJ03.pdf

Boehner, K., DePaula, R., Dourish, P., & Sengers, P. (2007). How emotion is made and measured. *International Journal of Human-Computer Studies, 65*(4), 275 - 291. Retrieved March 07, 2018, from http://www.sciencedirect.com/science/article/pii/S1071581906001844

Bohn, D. (2016, September 06). *Intel is buying the computer vision company that powers Tango and DJI's drones*. (The Verge) Retrieved January 23, 2017, from http://www.theverge.com/2016/9/6/12803652/intel-buying-movidius-tango-dji-phantom-computer-vision-chip

Bond, R., Zheng, H., Wang, H., Mulvenna, M., McAllister, P., Delaney, K., . . . Engel, F. (2017). SenseCare: Using Affective Computing to Manage and Care for the Emotional Wellbeing of Older People. In K. Giokas, L. Bokor,

& F. Hopfgartner, *eHealth 360°. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering* (Vol. 181). Springer. Retrieved September 14, 2017, from https://link.springer.com/chapter/10.1007/978-3-319-49655-9_42

Bowden, Z. (2016, October 12). *Might this be the cancelled Microsoft Band 3?* Retrieved February 01, 2017, from http://www.windowscentral.com/cancelled-microsoft-band-3

Bradley, M. M., & Lang, P. J. (1999). *Affective norms for English words (ANEW): Instruction manual and affective ratings.* Florida: The Center for Research in Psychophysiology, University of Florida.

Bradley, M. M., & Lang, P. J. (2017). *Affective Norms for English Words (ANEW)*. (University of Florida) Retrieved February 06, 2017, from http://csea.phhp.ufl.edu/media/anewmessage.html

Bradley, M., & Lang, P. (1994, March 25). Measuring Emotion: The Self-Assessment Manikin and the Semantic Differential. *Journal of behaviour therapy and experimental psychiatry, 25*(1), 49 - 59. Retrieved March 04, 2018, from http://www.ncbi.nlm.nih.gov/pubmed/7962581

Brownlee, J. (2014, March 21). *Classification Accuracy is Not Enough: More Performance Measures You Can Use.* Retrieved March 11, 2017, from http://machinelearningmastery.com/classification-accuracy-is-not-enough-more-performance-measures-you-can-use/

Brownlee, J. (2016, April 25). *Boosting and AdaBoost for Machine Learning.* Retrieved March 13, 2017, from http://machinelearningmastery.com/boosting-and-adaboost-for-machine-learning/

Brownlee, J. (2016, April 08). *Classification And Regression Trees for Machine Learning.* Retrieved March 13, 2017, from http://machinelearningmastery.com/classification-and-regression-trees-for-machine-learning/

Brownlee, J. (2016, April 15). *K-Nearest Neighbors for Machine Learning.* Retrieved March 13, 2017, from http://machinelearningmastery.com/k-nearest-neighbors-for-machine-learning/

Brownlee, J. (2018, May 30). *Classification Accuracy is Not Enough: More Performance Measures You Can Use.* Retrieved from Machine Learning Mastery: https://machinelearningmastery.com/classification-accuracy-is-not-enough-more-performance-measures-you-can-use/

Brunet-Gouet, E., Oker, A., Martin, J. C., Grynszpan, O., & Jackson, P. L. (2015). Editorial: Advances in Virtual Agents and Affective Computing for the Understanding and Remediation of Social Cognitive Disorders. *Frontiers in Human Neuroscience, 9*, 697. Retrieved December 05, 2016, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4703779/

BTS BioEngineering. (2017). *BTS FREEEMG*. Retrieved March 15, 2017, from http://www.btsbioengineering.com/products/surface-emg/bts-freeemg/

Burkhardt, F., Kienast, M., Paeschke, A., & Weiss, B. (2017). *Berlin Database of Emotional Speech (Emo-DB)*. Retrieved March 20, 2017, from http://emodb.bilderbar.info/start.html

Burns, J. (2017, April 12). *Neuro-Sensitive Foam Shows Your Expression In VR Before Your Face Does.* Retrieved February 03, 2018, from https://www.forbes.com/sites/janetwburns/2017/04/12/this-neuro-sensitive-foam-insert-is-changing-the-face-of-vr/#5327e8e33773

Business Insider. (2015, May 13). *The Robotics Market Report: The fast-multiplying opportunities in consumer, industrial, and office robots.* Retrieved July 09, 2015, from http://uk.businessinsider.com/growth-statistics-for-robots-market-2015-2?r=US

Cabibihan, J., & Chauhan, S. (2017, January - March). Physiological Responses to Affective Tele-Touch. *IEEE Transactions on Affective Computing, 8*(1), 108 - 118.

Caelers, R., & Penners, R. (2017, May 05). *Workrave*. Retrieved May 05, 2017, from http://www.workrave.org/

Calvo, A., & D'Mello, S. (2010). Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications. *IEEE Transactions on Affective Computing, 1*(1), 18 - 37. Retrieved January 21, 2018, from http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5520655

Calvo, R. A., D'Mello, S. K., Gratch, J., & Kappas, A. (2015). *Oxford Handbook of Affective Computing.* Oxford University Press . Retrieved March 10, 2017, from https://rafael-calvo.com/oxford-handbook-of-affective-computing/

Car, J., Tan, W. S., Huang, Z., Sloot, P., & Franklin, B. D. (2017). eHealth in the future of medications management: personalisation, monitoring and adherence. *BMC Medicine, 15*(1).

Carnegie Mellon University. (2018, January 24). *Depression Assessment*. Retrieved January 03, 2018, from https://www.ri.cmu.edu/robotics-area/depression-assessment/

Castelvecchi, D. (2017, January 03). *Quantum computers ready to leap out of the lab in 2017.* Retrieved February 17, 2017, from http://www.nature.com/news/quantum-computers-ready-to-leap-out-of-the-lab-in-2017-1.21239

CERC. (2017, May 13). *Collaborative European Research Conference (CERC)*. Retrieved May 13, 2017, from http://www.cerc-conference.eu/

Chatziantoniou, D., & Doukidis, G. (2009). Data Streams as an Element of Modern Decision Support. In *Encyclopedia of Information Science and Technology, Second Edition* (pp. 941 - 949). IGI Global.

Chaudhary, U., Xia, B., Silvoni, S., Cohen, L. G., & Birbaumer, N. (2017). Brain–Computer Interface–Based Communication in the Completely Locked-In State. *PLOS Biology, 15*(1), 1 - 25. Retrieved December 29, 2017, from http://journals.plos.org/plosbiology/article?id=10.1371/journal.pbio.1002593

Chia-Hsun, J. L., Wetzel, J., & Selker, T. (2006). Enhancing interface design using attentive interaction design toolkit. *ACM SIGGRAPH 2006 Educators program.* Boston, Massachusetts.

Clare, L., Worgan, P., Stark, B. H., Adami, S.-E., & Coyle, D. (2015). Influence of exposure guidelines on the design of on-body inductive power transfer. *2015 IEEE Wireless Power Transfer Conference (WPTC).* Boulder, USA: IEEE.

Clynes, D. M. (1977). *Sentics: The Touch of the Emotions.* Anchor Press/Doubleday.

Colman, A. M. (2015, March 08). Galvanic Skin Response (GSR). In *Oxford Dictionary of Psychology.* Retrieved March 08, 2017, from http://www.oxfordreference.com/search?source=%2F10.1093%2Facref%2F9780199657681.001.0001%2Facref-9780199657681&q=Galvanic+Skin+Response

Colombetti, G. (2014). *The Feeling Body: Affective Science Meets the Enactive Mind.* MIT Press.

ConvertUnits.com. (2017, August 15). *Measurement unit conversion: microsiemens*. Retrieved March 16, 2018, from ConvertUnits.com: https://www.convertunits.com/info/microsiemens

Cork Institute of Technology (CIT). (2017, May 17). *CIT to Host ISU 30th Space Studies Programme*. Retrieved February 27, 2018, from Cork Institute of Technology (CIT): http://www.cit.ie/currentnews?id=1212

Cork Institute of Technology. (2017). *Cork Institute of Technology (CIT)*. Retrieved February 17, 2017, from http://www.cit.ie/

Cowie, R. (2015). Ethical Issues in Affective Computing. In *The Oxford Handbook of Affective Computing.* Oxford University Press. Retrieved December 05, 2016, from http://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780199942237.001.0001/oxfordhb-9780199942237-e-006#oxfordhb-9780199942237-e-006-div2-8

Creative Labs. (2013, September 04). *Creative Senz3D depth and gesture camera setup video*. Retrieved October 12, 2017, from YouTube: https://www.youtube.com/watch?v=Kms0zEXpYN4

Cytowic, R. E. (1996). *The Neurological Side of Neuropsychology.* Cambridge, MA: MIT Press.

D'Mello, S. K., & Kory, J. (2015, April). A review and meta-analysis of multimodal affect detection. *ACM Computing Surveys, 47*(3). doi:10.1145/2682899

da Silva, H. P., Holzinger, A., Fairclough, S., & Majoe, D. (2014). *Physiological Computing Systems.* Springer. Retrieved March 10, 2017, from http://www.springer.com/gp/book/9783662456859

Dailey, M. N., Joyce, C., Lyons, M. J., Kamachi, M., Ishi, H., Gyoba, J., & Cottrell, G. W. (2010). Evidence and a computational explanation of cultural differences in facial expression recognition. *Emotion, 10*(6), 874 - 893.

Damasio, A. R. (1994). *Descartes' Error: Emotion, Reason, and the Human Brain.* New York NK: Gosset/Putnan Press.

Dan-Glauser, E. S., & Scherer, ,. K. (2011). The Geneva affective picture database (GAPED): a new 730-picture database focusing on valence and normative significance. *Behavior Research Methods, 43*(2), 468-477. doi:10.3758/s13428-011-0064-1

Darwin, C. (1872). *The Expression of the Emotions in Man and Animals.* Chicago, IL, 1965: The University of Chicago Press.

Darwin-Online.org and Dr John van Wyhe. (2017, March 31). *Darwin Online*. Retrieved March 31, 2017, from http://darwin-online.org.uk/content/frameset?pageseq=2&itemID=F1142&viewtype=side

Dasarathy, B. (1997). Sensor fusion potential exploitation: Innovative architectures and illustrative approaches. *IEEE Proceedings*, *85*, pp. 24 - 38.

De Roure, D. (Ed.). (2014). The future of scholarly communications. *Insights, 27*(3).

Delft University, Netherlands. (2017). *MMI Facial Expression Database*. Retrieved January 18, 2017, from http://mmifacedb.eu/pages/about/

Deyo, R. A., & et al. (2014). *Report of the NIH Task Force on research standards for chronic low back pain.* American Pain Society. Retrieved February 10, 2017, from https://www.ncbi.nlm.nih.gov/pubmed/25639530

Dictionary.com. (2017). *Human Computer Interaction*. Retrieved February 17, 2017, from http://www.dictionary.com/browse/human-computer-interaction

Doherty, I., Sharma, N., & Harbutt, D. (2015). Contemporary and future eLearning trends in medical education. *Medical Teacher, 37*(1).

Dorrier, J. (2016, June 28). *Smart Dust Is Coming.* Retrieved March 08, 2017, from Singularity University: https://singularityhub.com/2016/06/28/smart-dust-is-coming-new-camera-is-the-size-of-a-grain-of-salt/

Draelos, M., Qiu, Q., Bronstein, A., & Sapiro, G. (2015). Intel Realsense = Real low cost gaze. *IEEE International Conference on Image Processing (ICIP)* (pp. 2520 - 2524). Quebec: IEEE. doi:10.1109/ICIP.2015.7351256

Ebe, Y., & Umemuro, H. (2015). Emotion Evoked by Texture and Application to Emotional Communication. *CHI 2015.* Seoul.

Ekman, P., & Friesen, W. (1978). *Facial Action Coding System: A Technique for the Measurement of Facial Movement.* Palo Alto California: Consulting Psychologists Press.

El-Sheikh, M., Erath, S. A., & Bagley, E. J. (2013). Parasympathetic nervous system activity and children's sleep. *Journal of Sleep Research, 22*(3).

Emotient. (2017, July 02). *Emotient - About*. Retrieved January 27, 2017, from https://imotions.com/press-release/emotient-and-imotions-partner-to-offer-unique-integrated-facial-expression-recognition/

Emotion & Pain Project. (2017). *The Emotion & Pain Project*. Retrieved March 15, 2017, from http://www.emo-pain.ac.uk/

Emotiv. (2017). *Emotiv*. Retrieved February 07, 2017, from http://emotiv.com/

Emotiv. (2017). *Emotiv - Detection Algorithms*. Retrieved February 07, 2017, from https://www.emotiv.com/the-science/

Empatica. (2016, December 05). *What should I know to use EDA data in my experiment?* Retrieved March 13, 2017, from https://support.empatica.com/hc/en-us/articles/203621955-What-should-I-know-to-use-EDA-data-in-my-experiment-

Empatica. (2017, April 15). *Empatica E4 - Device Certification*. Retrieved April 15, 2017, from https://www.empatica.com/e4-wristband

Empatica. (2017). *Empatica E4 Wristband*. Retrieved February 01, 2017, from https://www.empatica.com/e4-wristband

Empatica. (2017, August 16). *What should I know to use the PPG/IBI data in my experiment?* Retrieved August 16, 2017, from Empatica Support: https://support.empatica.com/hc/en-us/articles/203621335-What-should-I-know-to-use-the-PPG-IBI-data-in-my-experiment-

Empatica. (2018, February 05). *Embrace is Now an FDA-approved Medical Device!* Retrieved March 10, 2018, from Empatica: https://blog.empatica.com/embrace-is-now-an-fda-approved-medical-device-bf506d991b1c

ENACT Consortium. (2015). *Enhancing Negotiation skills through on-line Assessment of Competencies and interactive mobile Training*. Retrieved March 16, 2017, from http://enactskills.eu/

Encyclopaedia Britannica. (2012, May 04). *Wilhelm Wundt - German Physiologist and Psychologist.* Retrieved January 10, 2017, from https://www.britannica.com/biography/Wilhelm-Wundt

Engel, F., Bond, R., Keary, A., Mulvenna, M., Walsh, P., Zheng, H., . . . Hemmje, M. (2016). SenseCare: Towards an Experimental Platform for Home-Based, Visualisation of Emotional States of People with Dementia. In *Road Mapping Infrastructures for Advanced Visual Interfaces Supporting Big Data in Springer Lecture Notes in Computer Science.* Springer.

Engel, F., Keary, A., Berwind, K., Bornschlegl, M. X., & Hemmje, M. (2017). The role of reproducibility in affective computing. *IEEE International Conference on Bioinformatics and Biomedicine (BIBM).* Kansas City, MO, USA: IEEE.

EU. (2015, August 11). *What is the Sixth Framework Programme?* Retrieved April 14, 2017, from https://ec.europa.eu/research/fp6/index_en.cfm

EU. (2018, January 07). *EU General Data Protection Regulation*. Retrieved January 07, 2018, from https://www.eugdpr.org/

EU Commission. (2017, May 05). *Research and Innovation Staff Exchange (RISE)*. Retrieved May 05, 2017, from https://ec.europa.eu/research/mariecurieactions/about/research-innovation-staff-exchange_en

European Agency for Safety and Health at Work. (2014, June 27). *Calculating the cost of work-related stress and psychosocial risks.* (E. A. Work, Ed.) Retrieved February 17, 2017, from European Agency for Safety and Health at Work: https://osha.europa.eu/en/publications/literature_reviews/calculating-the-cost-of-work-related-stress-and-psychosocial-risks/view

European Commission. (1989, June 12). *Directive 89/391/EEC - OSH "Framework Directive".* Retrieved February 17, 2017, from https://osha.europa.eu/en/legislation/directives/the-osh-framework-directive/1

European Commission. (2013, December 11). *Horizon 2020 calls for eHealth projects launched*. (EC) Retrieved March 23, 2018, from http://ec.europa.eu/digital-agenda/en/news/first-horizon-2020-calls-ehealth-projects-launched

European Commission. (2014, July 23). *ICT 2015 - Information and Communications Technologies - Robotics*. (EC) Retrieved April 17, 2015, from http://ec.europa.eu/research/participants/portal/desktop/en/opportunities/h2020/topics/9087-ict-24-2015.html

European Commission. (2014, July 23). *Internet of Things and Platforms for Connected Smart Objects.* Retrieved February 05, 2015, from http://ec.europa.eu/research/participants/portal/desktop/en/opportunities/h2020/topics/9091-ict-30-2015.html

European Commission. (2015). *Human Brain Project*. Retrieved February 05, 2015, from https://www.humanbrainproject.eu/participate/horizon-2020

European Commission. (2017). *Internet of Things and Platforms for Connected Smart Objects.* Retrieved February 07, 2017, from http://ec.europa.eu/research/participants/portal/desktop/en/opportunities/h2020/topics/ict-30-2015.html

EyeTech Digital Systems, Inc. (2017). *EyeTech Digital Systems.* Retrieved March 15, 2017, from http://www.eyetechds.com/

Faggella, D. (2015, August 25). *AI is So Hot, We've Forgotten All About the AI Winter*. (SINGULARITY) Retrieved February 17, 2017, from https://www.singularityweblog.com/ai-is-so-hot-weve-forgotten-all-about-the-ai-winter/

Feldman-Barrett, L., & Gross, J. J. (2013). *The Emerging Field of Affective Science.* Retrieved January 10, 2017, from http://www.psychologicalscience.org/observer/the-emerging-field-of-affective-science#.WHT4x9KLRdg

Felten, E. (2016, May 03). *Preparing for the Future of Artificial Intelligence.* Retrieved February 23, 2018, from Obama White House: https://obamawhitehouse.archives.gov/blog/2016/05/03/preparing-future-artificial-intelligence

Ferrari, M., & Quaresima, V. (2012, November). A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application. *NeuroImage, 63*(2), 921-935. Retrieved March 14, 2017, from http://www.sciencedirect.com/science/article/pii/S1053811912003308

Field, A., & Hole, G. (2011). Experimental Design. In *How to Design and Report Experiments* (pp. 54 - 104). SAGE Publications.

Free Dictionary. (2017, March 11). *Oxygen saturation*. (Farlex) Retrieved March 11, 2017, from http://medical-dictionary.thefreedictionary.com/oxygen+saturation

Friedman, J., Hastie, T., & Tibshirani, R. (2000). Additive logistic regression: A statistical view of boosting. In J. Friedman, T. Hastie, & R. Tibshirani, *Annals of Statistics* (pp. 337–407).

Fu, Y., VaLeong, H., Ngai, G., Huang, M. X., & Chan, S. C. (2014). Physiological Mouse: Towards an Emotion-Aware Mouse. *2014 IEEE 38th Annual International Computers, Software and Applications Conference Workshop.*

Gallagher, J. (2017, February 01). *Completely 'locked-in' patients can communicate.* Retrieved February 01, 2018, from BBC: http://www.bbc.com/news/health-38761461

Garbarino, M., Lai, M., Bender, D., Picard, R. W., & Tognetti, S. (2014). Empatica E3 — A wearable wireless multi-sensor device for real-time computerized biofeedback and data acquisition. *4th International Conference on Wireless Mobile Communication and Healthcare - Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH)* (pp. 39 - 42). Athens: IEEE. doi:10.1109/MOBIHEALTH.2014.7015904

Gartner. (2016, August 16). *Gartner's 2016 Hype Cycle for Emerging Technologies.* Retrieved March 08, 2016, from http://www.gartner.com/newsroom/id/3412017

Gartner. (2017, March 08). *Gartner Hype Cycle.* Retrieved March 08, 2017, from http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp

Genetics Home Reference. (2017). *ADRA2B gene*. Retrieved March 14, 2017, from https://ghr.nlm.nih.gov/gene/ADRA2B#resources

Geneva Emotion Research Group. (2013, December 06). *Emotion Analyst*. Retrieved September 13, 2017, from Geneva Emotion Research Group - Emotion Analyst: http://www.unige.ch/fapse/emotion/demo/TestAnalyst/GERG/apache/htdocs/start.php?lang=en

Ghaderi, A., Frounchi, J., & Farnam, A. (2015). Machine Learning-based Signal Processing Using Physiological Signals for Stress Detection. *22nd Iranian Conference on Biomedical Engineering (ICBME 2015)* (pp. 93 - 98). Tehran: Iranian Research Organization for Science and Technology.

Gil, R., Virgili-Gomá, J., García, R., & Mason, C. (2015). Emotions ontology for collaborative modelling and learning of emotional responses. *Computers in Human Behavior*(51), 610 - 617.

Girard, J., & Cohn, J. (2015). Automated audiovisual depression analysis. *Current Opinion in Psychology, 4*, 75 - 79. Retrieved January 24, 2018, from (http://www.sciencedirect.com/science/article/pii/S2352250X14000219

Glaser, A. (2017, March 27). *Elon Musk wants to connect computers to your brain so we can keep up with robots.* Retrieved January 24, 2018, from RECODE: https://www.recode.net/2017/3/27/15079226/elon-musk-computers-technology-brain-ai-artificial-intelligence-neural-lace

Goasduff, L. (2018, January 22). *Emotion AI Will Personalize Interactions.* Retrieved February 23, 2018, from Smarter with Gartner: https://www.gartner.com/smarterwithgartner/emotion-ai-will-personalize-interactions/

Gong, K. (2016, October 24). *Best practices for custom classifiers in Watson Visual Recognition*. (IBM) Retrieved January 25, 2017, from https://www.ibm.com/blogs/bluemix/2016/10/watson-visual-recognition-training-best-practices/

Goodman, B., & Flaxman, S. (2018, January 07). *European Union regulations on algorithmic decision-making and a "right to explanation"*. Retrieved January 07, 2018, from Cornell University Library: https://arxiv.org/abs/1606.08813

Google. (2017). *Cloud Vision API - Derive insight from images with our powerful Cloud Vision API*. Retrieved January 25, 2017, from https://cloud.google.com/vision/

Google. (2017). *Google Glass - Platform Overview*. Retrieved January 27, 2017, from https://developers.google.com/glass/develop/overview

Google. (2018, May 10). *Classification: ROC and AUC*. Retrieved June 02, 2018, from Machine Learning Crash Course: https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc

Google. (2018, February 01). *Connectivity Woven Into Everyday Essentials*. Retrieved February 01, 2018, from Jacquard: https://atap.google.com/jacquard/about/

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings National Academy of Science*, *101*, pp. 5228 - 5235. USA. Retrieved July 29, 2015, from http://psiexp.ss.uci.edu/research/papers/sciencetopics.pdf

Gundecha, P. (2016, October 6). *IBM Watson just got more accurate at detecting emotions*. (IBM) Retrieved January 25, 2017, from https://www.ibm.com/blogs/bluemix/2016/10/watson-has-more-accurate-emotion-detection/

Hadjidimitriou, S. K., & Hadjileontiadis, L. J. (2012). Toward an EEG-Based Recognition of Music Liking Using Time-Frequency Analysis,. *IEEE Transactions on Biomedical Engineering, vol. 59, no. 12, pp., 59*(12), 3498 - 3510. Retrieved March 13, 2017, from http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6313893&isnumber=6361493

Happy, S. L., & Routray, A. (2015). Automatic Facial Expression Recognition Using Features of Salient Facial Patches. *IEEE Transactions on Affective Computing, 6*(1), 1 - 12.

Hardesty, L. (2016, October 27). *Making computers explain themselves.* Retrieved February 23, 2018, from MIT News: http://news.mit.edu/2016/making-computers-explain-themselves-machine-learning-1028

Harvard University. (2017, January). *Are wristwatch-style heart rate monitors accurate?* Retrieved April 06, 2017, from http://www.health.harvard.edu/heart-health/are-wristwatch-style-heart-rate-monitors-accurate

Hastings, J., Ceusters, W., Smith, B., & Mulligan, K. (2011). Dispositions and Processes in the Emotion Ontology. *International Conference on Biomedical Ontology.* Buffalo, NY USA.

Health Level Seven International (HL7). (2017, September 06). *Health Level Seven International (HL7)*. Retrieved September 06, 2017, from Health Level Seven International (HL7): http://www.hl7.org/index.cfm?ref=nav

Healy, M., Keary, A., & Walsh, P. (2016). Prototype proof of concept for a mobile agitation tracking system for use in elderly and dementia care use cases. *Collaborative European Research Conference (CERC).* Cork.

Healy, M., Keary, A., & Walsh, P. (2017). Preforming real-time emotion classification using an Intel RealSense camera, multiple facial expression databases and a Support Vector Machine. *Collaborative European Research Conference (CERC 2017)* (pp. 156 - 167). Karlsruhe, Germany: CERC 2017. Retrieved February 09, 2018, from http://www.cerc-conference.eu/proceeding/

Heath, A. (2017, January 11). *Facebook has a mysterious team working on tech that sounds a lot like mind reading.* Retrieved January 24, 2018, from Business Insider: http://uk.businessinsider.com/facebooks-building-8-working-on-brain-computer-communication-platform-2017-1?r=US&IR=T

Hemodynamic Society. (2017). *What is Hemodynamics*. Retrieved March 20, 2017, from http://www.hemodynamicsociety.org/hemodyn.html

Hernandez, J., Hoque, M. E., Drevo, W., & Picard, R. W. (2012). Mood Meter: Counting Smiles in the Wild. *Proceedings of International Conference on Ubiquitous Computing (Ubicomp).* Pittsburgh, PA, USA. Retrieved January 18, 2017, from http://moodmeter.media.mit.edu/

Hernandez, J., McDuff, D., Benavides, X., Amores, J., Maes, P., & Picard, R. (2014). AutoEmotive: Bringing Empathy to the Driving Experience to Manage Stress. In ACM (Ed.), *Proceedings of the 2014 companion publication on Designing Interactive Systems (DIS '14)* (pp. 53 - 56). Vancouver: ACM. doi:10.1145/2598784.2602780

Hernandez, J., Morris, R. R., & Picard, R. W. (2011). Call Center Stress Recognition. In S. D. al., *ACII 2011, Part 1* (pp. 125 – 134). Berlin

Heidelberg: Springer-Verlag. Retrieved October 14, 2015, from http://affect.media.mit.edu/pdfs/11.Hernandez-Morris-Picard-ACII.pdf

Höflinger, F., Müller, J., Zhang, R., Reindl, L. M., & Burgard, W. (2013). A Wireless Micro Inertial Measurement Unit (IMU). *IEEE Transactions on Instrumentation and Measurement, 62*(9), 2583 - 2595. doi:doi: 10.1109/TIM.2013.2255977

Hong, K., Lee, S., Lim, Y., & Park, K. (2012). Measuring skin conductance over clothes. *Medical & Biological Engineering & Computing, 50*(11), 1155 - 1161. doi:doi:10.1007/s11517-012-0926-4

Hosseini, S. A., Khalilzadeh, M. A., Naghibi-Sistani, M. B., & Niazmand, V. (2010). Higher Order Spectra Analysis of EEG Signals in Emotional Stress States. *2010 Second International Conference on Information Technology and Computer Science*, (pp. 60 - 63). Kiev. Retrieved March 13, 2017, from http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5557329&isnumber=5557095

IBM. (2016, October 28). IBM Watson Visual Recognition Demo. Retrieved March 09, 2017, from https://www.youtube.com/watch?v=U-yJYHks1_s

IBM. (2017, June 12). *AI and cognitive computing*. (IBM) Retrieved November 22, 2016, from http://www.research.ibm.com/cognitive-computing/

IBM. (2017). *Go beyond artificial intelligence with Watson*. Retrieved January 23, 2017, from https://www.ibm.com/watson/

IBM. (2017). *IBM Watson Analytics for Social Media*. Retrieved March 14, 2017, from https://www.ibm.com/us-en/marketplace/social-media-data-analysis

IDC. (2017, March 20). *About International Data Corporation (IDC)* . Retrieved March 20, 2017, from https://www.idc.com/about/about.jsp

IEEE. (2017, March 10). *IEEE Transactions on Affective Computing*. Retrieved March 10, 2017, from http://ieeexplore.ieee.org/xpl/RecentIssue.jsp?punumber=5165369

iMotions. (2015, August 08). *MythBusters Dangerous Driving Episode.* Retrieved March 15, 2017, from https://imotions.com/mythbusters-dangerous-driving/

iMotions. (2017). *GSP Pocket Guide.* iMotions.

iMotions. (2017, March 15). *iMotions*. Retrieved March 15, 2017, from https://imotions.com/about/

iMotions. (2017). *iMotions - Automatic Facial Expression Analysis*. Retrieved January 27, 2017, from https://imotions.com/facial-expressions/

iMotions. (2017). *iMotions Publications.* Retrieved February 13, 2017, from https://imotions.com/resources/publications/#imotions_sensor=facial-expressions&imotions_department=medical

Intel. (2016, May 26). *Intel Acquires Computer Vision for IOT, Automotive*. Retrieved January 18, 2017, from https://newsroom.intel.com/editorials/intel-acquires-computer-vision-for-iot-automotive/

Intel. (2017, December 29). *Intel Euclid Community*. Retrieved December 29, 2017, from Intel Euclid Community: http://www.euclidcommunity.intel.com/

Intel. (2017, September 06). *Intel® RealSense™ Camera SR300*. Retrieved September 06, 2017, from http://www.mouser.com/pdfdocs/intel_realsense_camera_sr300.pdf

Intel. (2017). *Intel® RealSense™ Developer Kit (R200)*. Retrieved March 14, 2018, from https://software.intel.com/en-us/realsense/previous

Intel. (2017). *Intel® RealSense™ Development Kit Featuring the ZR300*. Retrieved March 14, 2017, from https://click.intel.com/intelr-realsensetm-development-kit-featuring-the-zr300.html

Intel. (2017). *Intel® RealSense™ SDK 2016 R2 Documentation*. Retrieved September 14, 2017, from https://software.intel.com/sites/landingpage/realsense/camera-sdk/v1.1/documentation/html/index.html?doc_face_face_landmark_data.html

Intel. (2017). *Intel® RealSense™ Technology*. Retrieved December 28, 2017, from http://www.intel.com/content/www/us/en/architecture-and-technology/realsense-overview.html

Intel. (2017, September 06). *Pose Euler Angles.* Retrieved September 06, 2017, from Intel Developer Zone: https://software.intel.com/sites/landingpage/realsense/camera-sdk/v1.1/documentation/html/index.html?poseeulerangles_pxcfacedata.html

Intel. (2018, February 01). *Intel RealSense D400 Depth Camera Series.* Retrieved February 01, 2018, from https://newsroom.intel.com/wp-content/uploads/sites/11/2018/01/realsense-d415-d435-fact-sheet.pdf

Intel. (2018, February 01). *Intel® RealSense™ SDK 2.0.* Retrieved February 01, 2018, from Intel: https://software.intel.com/en-us/realsense/sdk

International Data Corporation (IDC). (2016, June 15). *IDC Forecasts Wearables Shipments to Reach 213.6 Million Units Worldwide in 2020 with Watches and Wristbands Driving Volume While Clothing and Eyewear Gain Traction* . Retrieved January 30, 2017, from http://www.idc.com/getdoc.jsp?containerId=prUS41530816

Internet of Things Consortium (IoTC). (n.d.). *About the Internet of Things Consortium (IoTC)*. Retrieved December 05, 2016, from http://iofthings.org/iotc/

Irish Research Council. (2015, June 25). *New Foundations Scheme 2013*. Retrieved March 08, 2017, from http://research.ie/awards/new-foundations-scheme-2013

IrrLicht. (2016, July 09). *Welcome to the Irrlicht Engine*. Retrieved March 16, 2017, from http://irrlicht.sourceforge.net/

Jane, H. (2011, October). *A Joyful & Malicious History Of 'Schadenfreude'*. Retrieved March 10, 2017, from https://theawl.com/a-joyful-malicious-history-of-schadenfreude-7ac799c5121e#.6055k1pyq

Jenke, R., Peer, A., & Buss, M. (2014). Feature Extraction and Selection for Emotion Recognition from EEG. *IEEE Transaction on Affective Computing, 5*(3), 327 - 339.

Jones, D. (2016, March 24). *The Blood Volume Pulse - Biofeedback Basics.* Retrieved September 07, 2017, from Fixxl Ltd: https://www.biofeedback-tech.com/articles/2016/3/24/the-blood-volume-pulse-biofeedback-basics

Kahn, M. S., Kahn, I. A., & Shafi, M. (2012). Keyboard and mouse interaction based mood measurement using artificial neural networks. *IEEE International Conference on Robotics and Artificial Intelligence.* Rawalpindi, Punjab, Pakistan.

Kairos. (2017). *Kairos - Build with Kairos' APIs & SDKs*. Retrieved January 27, 2017, from https://www.kairos.com/docs/

Kairos. (2017). *Kairos - Face analysis made simple*. Retrieved January 27, 2017, from https://www.kairos.com/

Kankanhalli, M. S., & Chua, T.-S. (2000). Video modeling using strata-based annotation. *IEEE MultiMedia, 7*(1), 68 - 74. doi:10.1109/93.839313

Karaki, H., & Polyzoev, V. (2014, February 27). *Demystifying Thermopile IR Temp Sensors.* Retrieved August 16, 2017, from Sensors OnLine: http://www.sensorsmag.com/components/demystifying-thermopile-ir-temp-sensors

Karg, M., Kühnlenz, K., & Buss, M. (2010, August). Recognition of Affect Based on Gait Patterns. *IEEE Transactions on Systems, Man, and Cybernetics—*

*Part B: Cybernetics, 40*(4), 1050 - 1061. doi:10.1109/TSMCB.2010.2044040

Keary, A. P., & Redfern, S. (2012, April-June). The Future Directions of the Conferencing and Collaboration Field. (IGI, Ed.) *International Journal of e-Collaboration,, 8*(2), 46-69. doi:DOI: 10.4018/jec.2012040104

Keary, A. P., & Walsh, P. (2013). Affective and Perceptive Computing for Computer Mediated Communication in Game Based Learning Applications. *Collaborative European Research Conference (CERC).* Cork. Retrieved November 14, 2013, from http://cerc.cit.ie/venue/

Keary, A. P., Redfern, S., & Walsh, P. (2013). Current Trends and Developments, Future Requirements, and Predictions for Computer Mediated Communications and E-Collaboration. In M. E. Jennex, *Knowledge Discovery, Transfer, and Management in the Information Age* (pp. 212 - 244). IGI - Global. doi:10.4018/978-1-4666-4711-4

Keary, A., & Walsh, P. (2014). A Case for Serious Games Engineered with Affective Computing Functionality [Oral presentation]. *Limerick Postgraduate Research Conference (LPRC).* Limerick. Retrieved 05 07, 2015, from https://limerickpostgraduateresearch.wordpress.com/press/

Keary, A., & Walsh, P. (2014). How Affective Computing Could Complement and Advance the Quantified Self for workshop "The Role of Quantified Self for Personal Healthcare (QSPH 2014)". *IEEE International Conference on Bioinformatics and Biomedicine (BIBM).* Belfast: IEEE. Retrieved May 07, 2015, from http://scm.ulster.ac.uk/~bibm/2014/

Keary, A., & Walsh, P. (2014). Role of Affective Computing in Game Based Learning. *Irish Symposium on Game Based Learning 2014.* Cork. Retrieved 05 07, 2015, from https://igblconference.wordpress.com/presenters2014/

Keary, A., & Walsh, P. (2016). Sensor Enabled Affective Computing for Enhancing Medical Care (SenseCare). *Measuring Behavior.* Dublin. Retrieved March 16, 2018, from http://www.measuringbehavior.org/mb2016/home

Keary, A., & Walsh, P. (2017). *SIGMA AAAC - Local Interest Group*. Retrieved March 18, 2017, from http://sigma.cit.ie/aaac

Keary, A., Di Ferdinando, A., Miglino, O., Pessoa, I., da Silva, L. M., & Walsh, P. (2015). Seriously Intelligent Communications Skills Mentor (Abstract, Presentation, Poster). *Brain Informatics and Health.* London. Retrieved October 16, 2015, from http://braininformatics.london/

Keary, A., Walsh, P., O'Byrne, D., Mozier, J., Lean, J., Di Fernindo, A., . . . Sica, L. S. (2016). Using Online Role-Playing Games for Entrepreneurship Training. In P. Rooney , & N. Whitton, *Game-Based Learning and the Power of Play: exploring evidence, challenges and future directions* (pp. 49-81). Newcastle upon Tyne: Cambridge Scholars Publishing.

Keary, A., Walsh, P., O'Byrne, D., Moizer, P., & Lean, J. (2013). Using Online-Role-Play-Games for Entrepreneurship Training. *Irish Symposium on Game Based Learning 2013.* Dublin. Retrieved December 11, 2013, from http://igbl2013.wordpress.com/programme/

Khaleghi, B., Khamis, A., Karray, F. O., & Razavi, S. N. (2013). Multisensor data fusion: A review of the state-of-the-art. *Information Fusion, 14*, 28 - 44.

Khronos Group. (2016, May 02). *OpenVX - Portable, Power-efficient Vision Processing*. Retrieved January 18, 2017, from https://www.khronos.org/openvx/

Kim , J., Lee, S., Kim, S., & Yoo, W. Y. (2011). Music Mood Classification Model Based on Arousal - Valence Values. In IEEE (Ed.), *13th International Conference on Advanced Communication Technology (ICACT)* (pp. 292 - 295). Korea: IEEE. Retrieved July 15, 2015, from http://ieeexplore.ieee.org/search/searchresult.jsp?newsearch=true&queryText=valence%20arousal%20model

Kistler, A., Mariauzouls, C., & von Berlepsch, K. (1998). Fingertip Temperature as an Indicator for Sympathetic Responses. *International Journal of Psychophysiology, 29*(1), 35-41. Retrieved March 11, 2017, from https://www.ncbi.nlm.nih.gov/pubmed/9641246

Knight, W. (2017, April 13). *The Financial World Wants to Open AI's Black Boxes.* Retrieved February 23, 2018, from The MIT Technology Review: https://www.technologyreview.com/s/604122/the-financial-world-wants-to-open-ais-black-boxes/

Knight, W. (2017, March 14). *The U.S. Military Wants Its Autonomous Machines to Explain Themselves.* Retrieved February 23, 2018, from MIT Technology Review: https://www.technologyreview.com/s/603795/the-us-military-wants-its-autonomous-machines-to-explain-themselves/

Konar, A., Halder, A., & Chakraborty, A. (2015). Introduction to Emotion Recognition. In *Emotion Recognition: A Pattern Analysis Approach* (pp. 1-45). John Wiley & Sons, Inc. doi:DOI: 10.1002/9781118910566.ch1

Kowohl, U., Engel, F., Walsh, P., Keary, A., Fuchs, M., & Hemmje , M. (2016). Towards lifecycle management of clinical records in health care environments. *Collaborative European Research Conference (CERC).* Cork.

Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A Review. *Biological Psychology, 84*(3), 394-421.

Kumar, S., & et al. (2013). Mobile Health Technology Evaluation: The mHealth Evidence Workshop. *American Journal of Preventive Medicine, 45*(2), 228-236.

Kunze, M., Joubert, G. R., & Grandinetti, L. (2015). *Big Data and High Performance Computing.* Ios Press.

Lamkin, P., & Charara, S. (2017, January 13). *The best smartglasses 2017: Snap, Vuzix, ODG, Sony & more*. (Wearable) Retrieved January 27, 2017, from https://www.wareable.com/headgear/the-best-smartglasses-google-glass-and-the-rest

Lava, N. (2016, January). *An Overview of Aphasia*. Retrieved March 03, 2018, from https://www.webmd.com/brain/aphasia-causes-symptoms-types-treatments#1

Learning About Electronics. (2017, September 07). *What is a Photodiode?* Retrieved September 07, 2017, from http://www.learningaboutelectronics.com/Articles/What-is-a-photodiode

Lefter, I., Burghouts, G. J., & Rothkrantz, L. J. (2016). Recognizing Stress Using Semantics and Modulation of Speech and Gestures. (IEEE, Ed.) *Transactions on Affective Computing, 7*(2), 162 - 175.

Leng, B., Liu, Y., Yu, K., Zhang, X., & Xiong, Z. (2016, October). 3D object understanding with 3D Convolutional Neural Networks. *Information Sciences, 366*, 188 - 201. Retrieved May 31, 2018, from https://www.sciencedirect.com/science/article/pii/S0020025515005812

Lexalytics. (2017). *Lexalytics - Salience*. Retrieved February 07, 2017, from https://www.lexalytics.com/salience/server

Li, S. Z., & Jain, A. (2009). *Encyclopedia of Biometrics.* Springer. Retrieved June 05, 2018, from https://books.google.ie/books?id=0bQbOYVULQcC&printsec=frontcover&dq=Encyclopedia+of+Biometrics&hl=en&sa=X&ved=0ahUKEwjroum0wrzbAhXCCsAKHWCkCKsQ6AEIJzAA#v=onepage&q=%22multiple%20M%20hypotheses%20given%20the%20decisions%20of%20multiple%20N%20sensors%20in%

Lightbody, K. (2016, June 20). *Meet The New Wave Of Wearables: Stretchable Electronics.* Retrieved February 01, 2018, from Fast Company: https://www.fastcompany.com/3060274/meet-the-new-wave-of-wearables-stretchable-electronics

Littlewort, G., Whitehill, J., Wu, T., Fasel, I., Frank, M., Movellan, J., & Bartlett, M. (2008). Computer expression recognition toolbox. *8th IEEE International Conference on Automatic Face & Gesture Recognition*, (pp. 298 - 305). Amsterdam. Retrieved 07 22, 2015, from http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=4813406

Live Science. (2017, June 12). *The Quantified Self*. Retrieved February 17, 2017, from http://www.livescience.com/topics/quantified-self

LiveJournal Inc. (2015, July 29). *LiveJournal*. (LiveJournal Inc) Retrieved July 29, 2015, from http://www.livejournal.com/

Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z., & Matthews, I. (2010). The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, (pp. 94 - 101).

Lundqvist, D., Flykt, A., & Ohman, A. (1998). The Karolinska directed emotional faces (KDEF) CD-ROM. Karolinska Institute, Department of Clinical Neuroscience, Psychology section.

Luneski, A., Bamidis, P. D., & Hitoglou-Antoniadou, M. (2008). Affective computing and medical informatics: state of the art in emotion-aware medical applications. *Studies in Health Technology and Informatics, 136*, 517-522.

Luneski, A., Konstantinidis, E., & Bamidis, P. D. (2010, April 22). Affective medicine. A review of affective computing efforts in medical informatics.

*Methods of Information in Medicine, 49*(3), 207-2018. Retrieved December 05, 2016, from https://www.ncbi.nlm.nih.gov/pubmed/20411209#

Lyons, M. J. (2010). *The Japanese Female Facial Expression (JAFFE) Database*. (Ritsumeikan University) Retrieved March 10, 2017, from The Japanese Female Facial Expression (JAFFE) Database: http://www.kasrl.org/jaffe.html

Lyons, M. J., Akemastu, S., Kamachi, M., & Gyoba, J. (1998). Coding Facial Expressions with Gabor Wavelets. *3rd IEEE International Conference on Automatic Face and Gesture Recognition*, (pp. 200 - 205).

MacLeod, C. M. (2015). *Encyclopedia of Color Science and Technology.* Springer. Retrieved October 28, 2017, from http://imbs.uci.edu/~kjameson/ECST/MacLeod_TheStroopEffect.pdf

Magnusson, A., Skaug, H. j., Nielsen, A., Berg, C. W., Kristensen, K., Maechler, M., . . . Brooks, M. E. (2017). glmmTMB: Generalized Linear Mixed Models using Template Model Builder. R package version 0.1.3. Retrieved March 12, 2018, from https://github.com/glmmTMB

Maheshwari, S. (2016, May 08). *Building Emotional Machines.* Retrieved March 08, 2017, from https://blog.tracxn.com/2016/05/17/building-emotional-machines/

Marr, B. (2016, September 30). *Big Data: 20 Mind-Boggling Facts Everyone Must Read*. (Forbes) Retrieved February 17, 2017, from Forbes: http://www.forbes.com/sites/bernardmarr/2015/09/30/big-data-20-mind-boggling-facts-everyone-must-read/#794f5c166c1d

Marr, B. (2016, March 23). *What Everyone Should Know About Cognitive Computing*. (Forbes) Retrieved December 05, 2016, from http://www.forbes.com/sites/bernardmarr/2016/03/23/what-everyone-should-know-about-cognitive-computing/#1d5010e15d6e

Martins, T. G. (2013, November 21). *Introduction to Principal Component Analysis (PCA).* Retrieved March 13, 2018, from Thiago G. Martins: https://tgmstat.wordpress.com/2013/11/21/introduction-to-principal-component-analysis-pca/

Masetic, Z., & Subasi, A. (2016). Congestive heart failure detection using random forest classifier. *Computer Methods and Programs in Biomedicine, 130*(July), 54 - 64. doi:http://dx.doi.org/10.1016/j.cmpb.2016.03.020

Massachusetts Institute of Technology (MIT). (2017). *Affective Computing MIT*. Retrieved April 14, 2017, from Affective Computing MIT: http://affect.media.mit.edu/

MathWorks. (2017). *Fuzzy Logic Controller*. (MathWorks) Retrieved February 03, 2017, from http://uk.mathworks.com/help/fuzzy/fuzzylogiccontroller.html?s_tid=srchtitle

MC10. (2017, March 13). *BioStampRC.* Retrieved March 13, 2017, from https://www.mc10inc.com/our-products/biostamprc

MC10. (2017). *MC10 Our Story - Our Mission*. Retrieved 2017 13, March, from https://www.mc10inc.com/our-story

McCambridge, J., Witton, J., & Elbourne, D. R. (2014). Systematic review of the Hawthorne effect: New concepts are needed to study research participation effects. *Journal of Clinical Epidemiology, 67*(3), 267–277. doi:http://doi.org/10.1016/j.jclinepi.2013.08.015

McCarthy, C., Pradhan, N., Redpath, C., & Adler, A. (2016). Validation of the Empatica E4 wristband. *Student Conference (ISC), 2016 IEEE EMBS International.* Ottawa, ON, Canada: IEEE. doi:10.1109/EMBSISC.2016.7508621

McDuff, D., el Kaliouby, R., Senechal, T., Amr, A., Cohn, J. F., & Picard, R. (2013). Affectiva-MIT Facial Expression Dataset (AM-FED): Naturalistic and Spontaneous Facial Expressions Collected "In-the-Wild". *IEEE Conference on Computer Vision and Pattern Recognition Workshops*, (pp. 881 - 888). Portland. doi:10.1109/CVPRW.2013.130

McDuff, M., Kaliouby, R., Senechal, T., Demirdjian, D., & Picard, R. (2014). Automatic measurement of ad preferences from facial responses gathered over the internet. *Image and Vision Computing, 32*(10), 630 - 640.

Merriam - Webster Medical Dictionary. (2017, March 17 ). *Parietal Lobes*. Retrieved March 13, 2017, from https://www.merriam-webster.com/dictionary/parietal%20lobes

Merriam-Webster. (2017, January 10). *Affective Definition*. Retrieved January 10, 2017, from https://www.merriam-webster.com/dictionary/affective

Merriam-Webster Medical Dictionary. (2017, March 11). *Medical Definition of psychogalvanic reflex*. Retrieved March 11, 2017, from https://www.merriam-webster.com/medical/psychogalvanic%20reflex

Mertz, L. (2016, January/February 2016). The End of Seizures and Depression? *IEEE Pulse*. Retrieved January 24, 2018, from https://pulse.embs.org/january-2016/the-end-of-seizures-and-depression/

Mesko, B. (2015). Managing Alzheimer's and Parkinson's Disease With Technology. Retrieved March 13, 2017, from https://www.youtube.com/watch?v=LYJZf_TKBSI

Mesko, B. (2017, March 13). *About The Medical Futurist*. Retrieved March 13, 2017, from http://medicalfuturist.com/about/

Meta Motion. (2017). *IGS-190 Mobile Motion Capture System*. Retrieved March 15, 2017, from https://metamotion.com/gypsy/IGS-190-mobile-motion-capture-system.html

Microsoft. (2015, July 07). *Kinect Face Tracking SDK*. Retrieved January 23, 2017, from https://msdn.microsoft.com/en-us/library/jj130970.aspx#ID4EWF

Microsoft. (2017). *Computer Vision API Version 1.0*. Retrieved September 14, 2017, from https://azure.microsoft.com/en-us/services/cognitive-services/computer-vision/

Microsoft. (2017). *Get started with the Microsoft Band SDK*. Retrieved March 09, 2017, from https://developer.microsoftband.com/bandSDK

Microsoft. (2017, August 04). *Get started with your Microsoft Band 2*. Retrieved June 01, 2018, from Microsoft Band Support: https://support.microsoft.com/en-us/help/4000514/band-2-get-started

Microsoft. (2017, March 15). *Kinect for Windows SDK - Face Tracking.* Retrieved March 15, 2017, from https://msdn.microsoft.com/en-ie/library/dn782034.aspx

Microsoft. (2017). *Microsoft Cognitive Services - Emotion API*. Retrieved September 14, 2017, from https://azure.microsoft.com/en-us/services/cognitive-services/emotion/

Microsoft. (2017). *Microsoft Cognitive Services - Face API*. Retrieved September 14, 2017, from https://azure.microsoft.com/en-us/services/cognitive-services/face/

Microsoft. (2017). *Microsoft Cognitive Services - Welcome*. Retrieved September 14, 2017, from https://www.microsoft.com/cognitive-services/en-us/documentation

Microsoft. (2017). *Microsoft Health App*. Retrieved February 01, 2017, from https://www.microsoft.com/microsoft-band/en-us/microsoft-health

Microsoft. (2017). *Microsoft Health Cloud*. Retrieved February 01, 2017, from https://developer.microsoftband.com/cloudAPI

Microsoft. (2017, October 12). *Multithreaded Pipe Server*. Retrieved October 12, 2017, from Microsoft MSDN: https://msdn.microsoft.com/en-us/library/windows/desktop/aa365588(v=vs.85).aspx

Microsoft. (2017, October 12). *Named Pipes*. Retrieved October 12, 2017, from Microsoft MSDN: https://msdn.microsoft.com/en-us/library/windows/desktop/aa365590(v=vs.85).aspx

Miglino, O., Di Ferdinando, A., Rega, A., & Beninca, B. (2007). SISINE: Teaching Negotiation Through A Multiplayer Online Role Playing Game. In D. Remenyi, *Proceedings of the 6th European Conference on E-Learning* (pp. 439 - 448).

Mitchell, B. (2017, August 30). *What Does UWB Mean?* Retrieved February 02, 2018, from LifeWire: https://www.lifewire.com/ultra-wide-band-817953

Mitchell, T. (1997). *Machine Learning.* McGraw-Hill.

MIX-AI. (2018, March 05). *MIX - AI*. Retrieved March 05, 2018, from World Summit and Conference on Artificial Intelligence and Machine Learning: https://www.mixsummit-ai.com/

Monkaresi, H., & Hussain, M. S. (2012). A Dynamic Approach for Detecting Naturalistic Affective States from Facial Videos during HCI. In M. Thielscher, & D. Zhang, *AI 2012: Advances in Artificial Intelligence* (pp. 170–181). Berlin: Springer Berlin Heidelberg.

Monkaresi, H., Bosch, N., A. Calvo, R., & D'Mello, S. K. (2017). Automated Detection of Engagement using Video-Based Estimation of Facial Expressions and Heart Rate. *IEEE Transactions on Affective Computing, 8*(1), 15 - 28. doi:DOI: 10.1109/TAFFC.2016.2515084

Montgomery, M. (2016, October 26). *The Future Of Health Care Is In Data Analytics.* Retrieved February 17, 2017, from http://www.forbes.com/sites/mikemontgomery/2016/10/26/the-future-of-health-care-is-in-data-analytics/#549571332f71

Muoio, D. (2015, November 20). *Japan is running out of people to take care of the elderly, so it's making robots instead*. Retrieved October 27, 2017, from Business Insider: http://uk.businessinsider.com/japan-developing-carebots-for-elderly-care-2015-11?r=US&IR=T

Murgia , M. (2016, January 15). *Affective computing: How 'emotional machines' are about to take over our lives*. Retrieved December 14, 2016, from http://www.telegraph.co.uk/technology/2016/01/21/affective-computing-how-emotional-machines-are-about-to-take-ove/

National Institute of Biomedical Imaging and Bioengineering (NIBIB). (2017, March 13). *About National Institute of Biomedical Imaging and Bioengineering (NIBIB)*. Retrieved March 13, 2017, from https://www.nibib.nih.gov/

National Institute of General Medical Sciences (NIGMS). (2017, March 13). *About National Institute of General Medical Sciences (NIGMS)*. Retrieved March 13, 2017, from https://www.nigms.nih.gov/About/Pages/default.aspx

National Institute of General Medical Sciences (NIGMS). (2017, March 13). *PhysioNet*. Retrieved March 13, 2017, from https://www.physionet.org/

National Institute of General Medical Sciences (NIGMS). (2017, March 13). *PhysioNetworks*. Retrieved March 13, 2017, from https://physionet.org/users/

National Institute of General Medical Sciences. (2017, March 13). *PhysioBank*. Retrieved March 13, 2017, from https://www.physionet.org/physiobank/

National Physical Laboratory. (2017, August 16). *SI Prefixes*. Retrieved August 16, 2017, from National Physical Laboratory: http://www.npl.co.uk/reference/measurement-units/si-prefixes/

Negroponte, N. (1995). *Being Digital.* New York NY: Alfred A. Knofp.

NeuroSky. (2017). *NeuroSky*. Retrieved February 07, 2017, from http://neurosky.com/biosensors/eeg-sensor/biosensors/

NeuroSky. (2017). *NeuroSky - Useful, Applicable Brain Activity Algorithms.* Retrieved February 07, 2017, from http://neurosky.com/biosensors/eeg-sensor/algorithms/

Newman, T. (2016, February 03). *Psychoneuroimmunology: laugh and be well*. Retrieved February 17, 2017, from http://www.medicalnewstoday.com/articles/305921.php

Ng, Y. Y., Khong, C. W., & Thwaites, H. (2012). A Review of Affective Design towards Video Games. *The World Conference on Design, Arts and Education (DAE-2012)*, (pp. 687-69). Antalya, Turkey. doi:10.1016/j.sbspro.2012.08.225

Nguyen, T., Phung, D., Dao, B., Venkatesh, S., & Berk, M. (2014). Affective and Content Analysis of Online Depression Communities. *IEEE Transactions on Affective Computing, 5*(3), 217 - 226.

Novak, D., Mihelj, M., & Munih, M. (2012, May). A survey of methods for data fusion and system adaptation using autonomic nervous system responses in physiological computing. *Interacting with Computers, 24*(3), 1 - 17.

Retrieved June 11, 2018, from https://www.sciencedirect.com/science/article/pii/S0953543812000379

Nunamaker, J. F., Chen, M., & Purdin, T. D. (1990). Systems Development in Information Systems Research. (IEEE, Ed.) *Journal of Management Information Systems, 7*, 89 - 106.

Nyssens, M., & Kerlin, J. (2005). Social Enterprise in Europe. Unpublished paper.

O'Connell, J. (2017, January 07). *Feeling lonely? You're far from alone*. Retrieved January 24, 2018, from Irish Times: https://www.irishtimes.com/life-and-style/people/feeling-lonely-you-re-far-from-alone-1.2924443

Oculus. (2017, March 16). *RakNet*. Retrieved March 16, 2017, from http://www.jenkinssoftware.com/index.old.html

Open GeoSpatial Consortium. (2018, January 07). *Semantic Sensor Network Ontology*. Retrieved January 07, 2018, from https://www.w3.org/TR/vocab-ssn/#intro

Open GeoSpatial Consortium. (2018, January 07). *Sensor Model Language (SensorML)*. Retrieved January 07, 2018, from http://www.opengeospatial.org/standards/sensorml

OpenCV. (2016, May 27). *Intel acquires Itseez*. Retrieved January 18, 2017, from http://opencv.org/intel-acquires-itseez.html

OpenCV. (2017, March 09). *Introduction to Support Vector Machines.* Retrieved March 10, 2017, from http://docs.opencv.org/2.4/doc/tutorials/ml/introduction_to_svm/introduction_to_svm.html

OpenCV. (2018, February 06). *Open Source Computer Vision (OpenCV)*. Retrieved March 10, 2017, from http://opencv.org/

Ortony, A., Clore, G., & Collins, A. (1990). *The Cognitive Structure of Emotions.* Cambridge: Cambridge University Press. Retrieved July 15, 2015, from http://www.cambridge.org/ie/academic/subjects/psychology/cognition/cognitive-structure-emotions

Österle, H., Becker, J., Frank, U., Hess, T., Karagiannis, D., Krcmar, H., . . . Sinz, E. J. (2011). Memorandum on design-oriented information systems research. *European Journal of Information Systems, 20*(1), 7 - 10. doi:doi:10.1057/ejis.2010.55 2011

Oxford Dictionaries. (2017, January 10). *Affective Computing.* Retrieved January 10, 2017, from https://en.oxforddictionaries.com/definition/affective_computing

Oxford Dictionaries. (2017, January 10). *Affective Definition*. Retrieved January 10, 2017, from https://en.oxforddictionaries.com/definition/affective

Oxford Dictionaries. (2017, June 12). *Definition of affective computing in English*. Retrieved February 17, 2017, from https://en.oxforddictionaries.com/definition/affective_computing

Oxford Dictionaries. (2017, March 10). *Electromyography*. Retrieved March 10, 2017, from https://en.oxforddictionaries.com/definition/electromyography

Oxford Dictionaries. (2017, March 10). *Electro-oculography*. Retrieved March 10, 2017, from https://en.oxforddictionaries.com/definition/electro-oculography

Oxford Dictionaries. (2017, March 10). *Magnetic resonance imaging*. Retrieved March 10, 2017, from https://en.oxforddictionaries.com/definition/magnetic_resonance_imaging

Oxford Press. (2015). Electrocardiogram. In *Oxford Concise Medical Dictionary.* Oxford Press. Retrieved March 08, 2017, from http://www.oxfordreference.com/search?q=ElectroCardioGram&searchBtn=Search&isQuickSearch=true

Oxford Reference. (2017, March 08). *Electroencephalography (EEG).* Retrieved March 08, 2017, from http://www.oxfordreference.com/view/10.1093/oi/authority.20110803095746352

Oximetry.org. (2002, September 10). *Principles of Pulse Oximetry Technology.* Retrieved February 01, 2018, from http://www.oximetry.org/pulseox/principles.htm

Pantic, M., Valstar, M., Rademaker, R., & Maat, L. (2005). Web-based database for facial expression analysis. *ICME 2005. IEEE International Conference on Multimedia and Expo.* doi:10.1109/ICME.2005.1521424

Patently Apple. (2016, April 19). *Apple Wins Patent for Advancing Touch Surfaces to Simulate Textures and Temperatures.* Retrieved March 20, 2017, from http://www.patentlyapple.com/patently-apple/2016/04/apples-wins-patent-for-advancing-touch-surfaces-to-simulate-textures-and-temperatures.html

Patil, J. V., & Bailke, P. (2016). Real time facial expression recognition using Real Sense camera and ANN. In IEEE (Ed.), *2016 International Conference on*

*Inventive Computation Technologies (ICICT)*, (pp. 1 - 6). Coimbatore. doi:doi: 10.1109/INVENTIVE.2016.7824820

Paul Ekman Group. (2015, July 18). *Paul Ekman*. Retrieved July 18, 2015, from http://www.paulekman.com/

Paul, W., Alphonsus, K., Matthias, H., Huiru, Z., & Riastra, R. (2015). *SenseCare (Sensory Enabled Affective Computing for Enhancing Medical Care) RISE Proposal.*

Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2007). Linguistic inquiry and word count (LIWC). *Linguistic inquiry and word count*. Pennebaker Conglomerates, Inc. Retrieved July 29, 2015, from http://www.liwc.net/

Petrantonakis, P. C., & Hadjileontiadis, L. J. (2010, March). Emotion Recognition From EEG Using Higher Order Crossings. *IEEE Transactions on Information Technology in Biomedicine, 14*(2), 186 - 197. Retrieved March 13, 2017, from http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5291724&isnumber=5431105

Picard , R. W., Fedor, S., & Ayzenberg , Y. (2016). Multiple Arousal Theory and Daily-Life Electrodermal Activity Asymmetry. *Emotion Review, 8*(1), 1-14.

Picard, R. (1997). *Affective Computing.* MIT Press Cambridge, MA, USA ©1997.

Picard, R. (2010, January-June). Affective Computing: From Laughter to IEEE. (IEEE, Ed.) *IEEE Transactions on Affective Computing, 1*(1), 11-17.

Picard, R. W., Fedor, S., & Ayzenberg, Y. (2016). Response to Commentaries on "Multiple Arousal Theory and Daily-Life Electrodermal Activity Asymmetry". *Emotion Review, 8*(1), 84 - 86.

PLOTTO. (n.d.). *How Emotion Analysis is Already Changing Lives*. Retrieved December 07, 2016, from http://news.plotto.com/blog/emotion-analysis-and-video-research

Poria, S., Cambria, E., Bajpai, R., & Hussain, A. (2017). A review of affective computing: From unimodal analysis to multimodal fusion. *Information Fusion, 37*, 98 - 125.

Qi-rong, M., Xin-yu, P., Yong-zhao, Z., & Xiang-jun, S. (2015, April 12). Using Kinect for real-time emotion recognition using facial expressions. *Frontiers of Information Technology & Electronic Engineering, 16*(04), 272 - 282. doi:10.1631/FITEE.1400209

Qt. (2017, March 16). *Qt for Application Development*. Retrieved March 16, 2017, from https://www.qt.io/qt-for-application-development/

Rahim, M. A. (1983). A Measure of Styles of Handling Interpersonal Conflict. *Academy of Management Journal, 26*, 368 - 376.

Ramakrishnan, N., & Kumar, R. (2016). Big Data. *Computer, 49*(4).

Reisenzein, R., Hudlicka, E., Dastani, M., Gratch, J., Hindriks, K., Lorini, E., & Meyer, J.-J. (2013). Computational Modeling of Emotion: Toward Improving the Inter- and Intradisciplinary Exchange. *IEEE - Transactions on Affective Computing, 4*(3), 246 - 266. doi:10.1109/T-AFFC.2013.14

Richardson, L., & Ruby, S. (2007). *Restful Web Services (First ed.).* O'Reilly.

Ringnér, M. (2008). What is principal component analysis? *Nature Biotechnology, 26*(3), 303 - 304. doi:doi:10.1038/nbt0308-303

Rogers Research Group. (2018, February 01). *Rogers Research Group*. Retrieved February 01, 2018, from http://rogersgroup.northwestern.edu/

Rosenberg, E. (2005). The Study of Spontaneous Facial Expressions in Psychology. In P. Ekman, & E. L. Rosenberg (Eds.), *What the Face Reveals - Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS)* (pp. 13 - 17). Oxford: Oxford Press. Retrieved July 17, 2015, from http://www.researchgate.net/profile/Francois_Dore/publication/15338544_Components_and_recognition_of_facial_expression_in_the_communication_of_emotion_by_actors/links/0deec52c6d617c04b6000000.pdf

Rouse, M. (2005, September). *Fourier analysis.* Retrieved March 13, 2017, from http://whatis.techtarget.com/definition/Fourier-analysis

Rozenfeld, M. (2016, June 01). *The Next Step for Artificial Intelligence Is Machines that Get Smarter on Their Own.* Retrieved February 23, 2018, from The Institute - IEEE News Source: http://theinstitute.ieee.org/technology-topics/artificial-intelligence/the-next-step-for-artificial-intelligence-is-machines-that-get-smarter-on-their-own

RStudio. (2018, March 09). *Take control of your R code*. Retrieved March 09, 2018, from RStudio: https://www.rstudio.com/products/rstudio/

RTE. (2017, April 20). *Facebook studying ways to control computers by thought*. Retrieved January 24, 2018, from https://www.rte.ie/news/2017/0420/868852-facebook/

Russell, J. (1980). A Circumplex Model of Affect. *Journal of Personality and Social Psychology, 39*(6), 1161 - 1178.

Ryan, A., Cohn, J. F., Lucey, S., Saragih, J., De La Torre, F., & Rossi, A. (2009). Automated Facial Expression Recognition System. *Conference on Security Technology, 2009. 43rd Annual 2009 International Carnahan*, (pp. 172 - 177). Zurich. Retrieved 07 18, 2015, from http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=5335546&url=http%3A%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D5335546

Sage Publishing. (2017). *Psychological Science*. Retrieved January 11, 2017, from https://uk.sagepub.com/en-gb/eur/journal/psychological-science#description

Sakr, E., Elhajj, I. H., & Huijer, H. A.-S. (2010). Support Vector Machines to Define and Detect Agitation Transition. *IEEE Transactions on Affective Computing, 1*(2), 98 - 108.

Samara, A., Galway, L., Bond, R., & Wang, H. (2017, December 04). Affective State Detection via Facial Expression Analysis within a Human-Computer Interaction Context. *Journal of Ambient Intelligence and Humanized Computing*, 1-10. Retrieved December 28, 2017, from https://link.springer.com/article/10.1007/s12652-017-0636-8#citeas

Sammut, C., & Webb, G. I. (2010). *Sensitivity and Specificity.* Springer US. doi:10.1007/978-0-387-30164-8_752

Sawh, M. (2017, January 09). *The best smart clothing: From biometric shirts to contactless payment jackets*. (Wareable) Retrieved May 17, 2017, from https://www.wareable.com/smart-clothing/best-smart-clothing

Schalkoff, R. J. (1997). *Artificial Neural Networks 1997.* McGraw-Hill.

Schatsky, D., Petrov, P., & Ronanki, R. (2015). *Cognitive technologies for health plan - Using artifical intelligence to meet new market demand.* United Kingdom: Deloitte University Press . Retrieved December 14, 2016, from https://dupress.deloitte.com/dup-us-en/focus/cognitive-technologies/artificial-intelligence-health-plans.html

Scherer, K. R. (2005). What are emotions? And how can they be measured. *Social Science Information, 44*(4), 695-729.

Schmidt, E., Decke, R., & Rasshofer, R. (2016). Correlation Between Subjective Driver State Measures and Psychophysiological and Vehicular Data in Simulated Driving. *Proceedings IEEE Intelligent Vehicles Symposium (IV)*, *2016 – August*, pp. 1380–1385. Gothenburg. Retrieved January 13, 2017, from http://ieeexplore.ieee.org/document/7535570/?tp=&arnumber=7535570&url=http:%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D7535570

ScienceDaily. (2017). *Sympathetic nervous system*. Retrieved February 01, 2017, from https://www.sciencedaily.com/terms/sympathetic_nervous_system.htm

SenseCare Consortium. (2016). *SenseCare - Sensor Enabled Affective Computing for Enhancing Medical Care*. Retrieved December 05, 2016, from http://www.sensecare.eu/

Shah, A. (2017, January 20). *New details emerge about Intel's super-small Euclid computer for robots*. Retrieved March 14, 2017, from http://www.pcworld.com/article/3159733/hardware/new-details-emerge-about-intels-super-small-euclid-computer-for-robots.html

Shih, J. J., Krusienski, D. J., & Wolpaw, J. R. (2012). Brain-Computer Interfaces in Medicine. *Mayo Clinic Proceedings*, *87*, pp. 268–279. doi:http://doi.org/10.1016/j.mayocp.2011.12.008

Shimmer. (2015, March). *Measuring Human Emotion: Reactions To Media Stimuli.* Retrieved March 13, 2017, from http://www.shimmersensing.com/case-studies/measuring-emotion-reactions-to-media

Shimmer. (2017). *Consensys GSR Development Kits*. (Shimmer) Retrieved February 01, 2017, from http://www.shimmersensing.com/menu/products/gsr-optical-pulse-development-kit

Shimmer. (2017). *Shimmer joint venture with Indian based ESSEN Electronic Systems*. Retrieved February 01, 2017, from http://www.shimmersensing.com/menu/about/wearable-technology-media/

Shimmer. (2017). *Shimmer NeuroLynQ.* Retrieved September 19, 2017, from Shimmer NeuroLynQ:

http://www.shimmersensing.com/images/uploads/docs/NeuroLynQ_Spec_Sheet.pdf

Shimmer. (2017). *Shimmer Publications*. Retrieved February 01, 2017, from http://www.shimmersensing.com/menu/support/publications/#1

SIGMA - Cork Institute of Technology (CIT). (2016). *Software Intelligence and Machine Intelligence Applications group (SIGMA)*. Retrieved July 28, 2016, from http://sigma.cit.ie/

Skiba, D. (2015). Connected Health: Preparing Practitioners. *Nursing Education Perspectives, 36*(3), 198 - 201. Retrieved February 17, 2017, from https://cit.summon.serialssolutions.com/search?SORT=%2BZ&sortdropdown=-&searchlimits=&page=search&searchMethod=2&searchtype=Y&q=Connected+Health#!/search?ho=t&l=en&SORT=%2BZ&sortdropdown=-&page=search&searchMethod=2&searchtype=Y&q=Connected%20Health

Smith, K. (2007, July 30). *Genes influence emotional memory*. (Nature) Retrieved February 07, 2017, from http://www.nature.com/news/2007/070730/full/news070730-1.html

Smith, T. A., & Pincever, N. C. (1991). Parsing Movies in Context. *Usenix Conference*, (pp. 157 - 168). Berkeley California.

Snoek, C. G., Worring, M., & Smeulders, A. W. (2005). Early versus late fusion in semantic video analysis. *13th Annual ACM International Conference on Multimedia*, (pp. 399–402).

SoftBank Robotics Corporation. (2015, June 20). *1,000 'Pepper' Units Sell Out in a Minute.* Retrieved July 09, 2015, from http://www.softbank.jp/en/corp/group/sbr/news/press/2015/20150620_01/

SparkFun. (2017, August 16). *Accelerometer Basics*. Retrieved August 16, 2017, from https://learn.sparkfun.com/tutorials/accelerometer-basics

Spires, H. A. (2015). Digital Game-Based Learning. *Journal of Adolescent & Adult Literacy, 59*(2), 125 - 130. Retrieved February 17, 2017, from http://pt4wp4eq4h.search.serialssolutions.com/?ctx_ver=Z39.88-2004&ctx_enc=info%3Aofi%2Fenc%3AUTF-8&rfr_id=info%3Asid%2Fsummon.serialssolutions.com&rft_val_fmt=info%3Aofi%2Ffmt%3Akev%3Amtx%3Ajournal&rft.genre=article&rft.atitle=Digital+Game%E2%80%90Based+

Stanford University. (2017, March 15). *Center for Automotive Research at Stanford.* Retrieved March 15, 2017, from https://cars.stanford.edu/

Statistics How To. (2018, May 29). *Sensitivity vs Specificity and Predictive Value.* Retrieved from Statistics How To: http://www.statisticshowto.com/sensitivity-vs-specificity-statistics/

Strongman, K. T. (2003). *The Psychology of Emotion: From Everyday Life to Theory.* Wiley.

Sukel, K. (2016, January 12). *Feeling Our Way: The Challenge of Studying Emotion and the Brain*. (BrainFacts.org) Retrieved December 12, 2016, from http://www.brainfacts.org/sensing-thinking-behaving/mood/articles/2016/feeling-our-way-the-challenge-of-studying-emotion-and-the-brain-011216/

Swiss Center for Affective Sciences. (2017, December 27). *Geneva Appraisal Questionnaire*. Retrieved December 27, 2017, from http://www.affective-sciences.org/files/3414/6658/8818/GAQ_English_0.pdf

Swiss Center for Affective Sciences. (2017, December 27). *The Geneva Emotion Wheel.* Retrieved April 07, 2017, from http://www.affective-sciences.org/gew

Swiss Centre for Affective Sciences. (2017). *Swiss Centre for Affective Sciences*. Retrieved March 18, 2017, from http://www.affective-sciences.org

Swiss Centre for Affective Sciences. (2018, January 01). *Adaptative Emotion Awareness Tools for Computer-Mediated INTeractions (EATMINT)*. Retrieved March 08, 2017, from http://www.affective-sciences.org/home/research/projects-and-foci/research-projects/eatmint/

Tao, Y., Wang, K., Yang, J., An, N., & Li, L. (2015). Harmony search for feature selection in speech emotion recognition. *ACII '15 Proceedings of the 2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*, (pp. 362 - 367). Xi'an.

TechTarget. (2017, August). *TCP/IP (Transmission Control Protocol/Internet Protocol).* Retrieved February 09, 2018, from http://searchnetworking.techtarget.com/definition/TCP-IP

Thayer, R. (1989). *The Biopsychology of Mood and Arousal.* Oxford University: Oxford University Press.

The Center for Digital Ethics and Policy. (2015, February 16). *Google Glass: Flawed Technology or Flawed Ethics?* (Centre for Digital Ethics and

Policy) Retrieved February 06, 2018, from http://www.digitalethics.org/essays/google-glass-flawed-technology-or-flawed-ethics

The Economist. (2012, May). The quantified self - Counting every moment. Retrieved February 17, 2017, from http://www.economist.com/node/21548493

The Future of Life Institute. (2018). *ASILOMAR AI Principles.* Retrieved February 23, 2018, from The Future of Life Institute: https://futureoflife.org/ai-principles/

The MathWorks Inc. (2017, March 13). *MatLab.* Retrieved March 13, 2017, from https://uk.mathworks.com/products/matlab.html

The Medical Futurist Institute. (2018, 01 24). *Should Algorithms and Robots Mimic Empathy?* Retrieved March 10, 2018, from Medical Futurist: http://medicalfuturist.com/algorithms-robots-mimic-empathy/

The R Foundation. (2018, March 09). *The R Project for Statistical Computing*. Retrieved March 09, 2018, from The R Foundation: https://www.r-project.org/

Tobii Group. (2017). *Tobii Eye Tracking.* Retrieved March 15, 2017, from http://www.tobii.com/

UNINA. (2017, May 08). *Università degli Studi di Napoli Federico II (UNINA)*. Retrieved May 08, 2017, from http://www.unina.it/home;jsessionid=B86B0FB18B9311CAAD6BEEE1E0E8E045.node_staging11

University of Michigan. (2018, February 01). *Michigan Micro Mote (M3) Makes History*. Retrieved March 16, 2018, from https://www.eecs.umich.edu/eecs/about/articles/2015/Worlds-Smallest-Computer-Michigan-Micro-Mote.html

University of Stirling and University of Aberystwyth. (2017, January 18). *Stirling/ESRC 3D Face Database*. Retrieved January 18, 2017, from http://pics.psych.stir.ac.uk/ESRC/examples.htm

Vankayallapati, H., Anne, K., & Kyamakya, K. (2011). Emotion recognition from decision level fusion of visual and acoustic features using Hausdorff classifier. *Communications in Computer and Information Science, 157*, 601 - 610.

Viola, P., & Jones, M. (2004). Robust real-time face detection. *International Journal of Computer Vision, 57*(2), 137 - 154.

Viola, P., & Jones, M. (2004). Robust real-time object detection. *International Journal of Computer Vision, 57*(2), 137 - 154.

Virdee-Chapman, B. (2017, January 9). *Face Recognition: Kairos vs Microsoft vs Google vs Amazon vs OpenCV*. Retrieved January 27, 2017, from https://www.kairos.com/blog/face-recognition-kairos-vs-microsoft-vs-google-vs-amazon-vs-opencv

Vizer, L., Zhou, L., & Sears, A. (2009). Automated stress detection using keystroke and linguistic features: An exploratory study. *International Journal of Human-Computer Studies, 67*, 870 - 886.

Vokorokos, L., Mihaľov, J., & Leščišin, L. (2016). Possibilities of depth cameras and ultra wide band sensor. *2016 IEEE 14th International Symposium on Applied Machine Intelligence and Informatics (SAMI)*, (pp. 57 - 61). Herlany. doi:10.1109/SAMI.2016.7422982

W3C. (2014, May 22). *Emotion Markup Language (EMOTIONML) 1.0 is a W3C Recommendation*. Retrieved September 13, 2017, from W3C: https://www.w3.org/blog/news/archives/3861

Wager, T. D., Kang, J., Johnson, T. D., Nichols, T. E., & Satpute, A. B. (2015). A Bayesian Model of Category-Specific Emotional Brain Responses. *PLoS Computational Biology, 11*(4). Retrieved December 12, 2016, from http://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1004066

Wagner, J., Lingenfelser, F., Andre, E., & Kim, J. (2011). Exploring Fusion Methods for Multimodal Emotion Recognition with Missing Data. *IEEE Transactions on Affective Computing, 2*(4), 206–218.

Wang, K., An, N., Li, B. N., Zhang, Y., & Li, L. (2015). Speech Emotion Recognition Using Fourier Parameters. *Transactions on Affective Computing, 6*(1), 69 - 74.

Webb, A. (2017, March 28). *Trump's Treasury secretary is an Artificial Intelligence denier.* Retrieved March 03, 2018, from http://www.latimes.com/opinion/op-ed/la-oe-webb-ai-mnuchin-20170328-story.html

Weisstein, E. W. (2017, August 15). *Euler Angles*. Retrieved August 15, 2017, from Wolfram MathWorld: http://mathworld.wolfram.com/EulerAngles.html

Wen, W., Liu, G., Cheng, N., Wei, J., Shangguan, P., & Huang, W. (2014). Emotion Recognition Based on Multi-Variant Correlation of Physiological Signals. *IEEE Transactions on Affective Computing, 5*(2), 126 - 140.

Whissell, C. M. (1989). The Dictionary of Affect in Language. In Academic. San Francisco, CA, USA: Academic. Retrieved March 05, 2018, from https://www.god-helmet.com/whissel-dictionary-of-affect/index.htm

White, F. E. (1991). *Data Fusion Lexicon, Joint Directors of Laboratories, Technical Panel for C3, Data Fusion Sub-Panel.* San Diego: Naval Ocean Systems Center.

Whitehill, J., Serpell, Z., Lin, Y. C., Foster, A., & Movellan, J. R. (2014). The Faces of Engagement: Automatic Recognition of Student Engagement from Facial Expressions. *IEEE Transactions on Affective Computing, 5*(1), 86 - 98.

Wicklund, E. (2016, October 26). *Digital Health With A Heart: mHealth Tech Looks to Measure Feelings*. Retrieved January 24, 2018, from mhealthintelligence.com: https://mhealthintelligence.com/news/digital-health-with-a-heart-mhealth-tech-looks-to-measure-feelings

Wimo, A., & Prince, M. (2010, 09 21). *World Alzheimer Report 2010 - The Global Economic Impact of Dementia.* Retrieved February 17, 2017, from http://www.alz.org/documents/national/world_alzheimer_report_2010.pdf

Wimo, A., Jönsson, L., & Gustavsson, A. (2009, 10 27). *Cost of illness and burden of dementia in Europe - Prognosis to 2030.* (A. Europe, Ed.) Retrieved April 23, 2015, from http://www.alzheimer-europe.org/Research/European-Collaboration-on-Dementia/Cost-of-dementia/Prognosis-to-2030

Winkler, R., Wakabayashi, D., & Dwoskin, E. (2016, January 07). *Apple Buys Artificial-Intelligence Startup Emotient*. (Wall Street Journal) Retrieved January 23, 2017, from http://www.wsj.com/articles/apple-buys-artificial-intelligence-startup-emotient-1452188715

Winston, P. H. (1993). *Artificial intelligence.* Addison-Wesley.

Wireless Power Consortium. (2017, September 20). *Inductive Power Transmission*. Retrieved September 20, 2017, from https://www.wirelesspowerconsortium.com/technology/basic-principle-of-inductive-power-transmission.html

WolframAlpha. (1999). *Fourier Parameters.* Retrieved March 13, 2017, from https://reference.wolfram.com/language/ref/FourierParameters.html

Xhyheri, B., Manfrini, O., Mazzolin, M., Pizzi, C., & Bugiardini, R. (2012). Heart Rate Variability Today. *Progress in Cardiovascular Diseases, 55*(3), 321 - 331. doi:http://dx.doi.org/10.1016/j.pcad.2012.09.001

XSENS. (2017, September 19). *Inertial sensors*. Retrieved September 19, 2017, from XSENS: https://www.xsens.com/tags/inertial-sensors/

Yang, K., Wang, K., Hu, W., & Bai, J. (2016). Expanding the Detection of Traversable Area with RealSense for the Visually Impaired. *Sensors, 16*(11).

Yang, S., Kafai, M., An, L., & Bhanu, B. (2014). Zapping Index: Using Smile to Measure Advertisement Zapping Likelihood. *IEEE Transactions on Affective Computing, 5*(4), 432 - 444.

Yannakakis, G. N., Isbister, K., Paiva, A., & Karpouzis, K. (2014). Guest Editorial: Emotion in Games. *IEEE Transactions on Affective Computing, 5*(1), 1-2. Retrieved December 14, 2016, from http://ieeexplore.ieee.org.cit.idm.oclc.org/stamp/stamp.jsp?tp=&arnumber=6812170&tag=1

Zeng, Z., Pantic, M., Roisman, G. I., & Huang, T. S. (2009). A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 31*(1), 39 - 58.

Zheng, Y.-L., Ding, X.-R., Yan Poon, C., Lai Lo, B., Zhang, H., Zhou, X.-L., . . . Zhang, Y.-T. (2014, May). Unobtrusive Sensing and Wearable Devices for Health Informatics. *IEEE Transactions on Biomedical Engineering, 61*(5).

Zhu, B. (2002). Visualizing a computer mediated communication (CMC) process to facilitate knowledge management. *CHI '02 Extended Abstracts on Human Factors in Computing Systems*, (pp. 562-563). Minneapolis, Minnesota, USA.

Zwass, V. (2017, August 17). *Agent - also called softbot ("software robot")*. Retrieved October 27, 2017, from Encyclopaedia Britannica: https://www.britannica.com/technology/agent

# 8 Appendices Section (See Volume 2 of 2)

Please see the thesis appendices document volume 2 of 2 for the following:

- Chapter four EFS software artifacts code extracts.
- Chapter five ethics documentation.
- Chapter five experiments documentation.
- Chapter five statistical reporting, analysis and evaluations.