EMind: Improve Group Effectiveness by Enhancing Social Sensitivity

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Introduction

Known as “the whole is greater than the sum of its parts” (*Group dynamics*, 2016), teamwork has become more important than ever before. According to Salas, Dickinson, Converse, and Tannenbaum (1992), team is “A distinguishable set of two or more people who interact, dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission, who have been assigned specific roles or functions to perform, and who have a limited life-span of membership” (Zaccaro, Rittman, and Marks, 2002). Through this definition, we understand that individuals in a team share a specific goal and have their own responsibilities. They cooperate with each other in order to accomplish the common goal, and the capacity of achieving the shared outcome is called “Team Effectiveness” (*Team effectiveness*, 2016).

A number of research about factors influencing team effectiveness and how to improve it have been conducted for many years. In 2012, Google initiated a Project named Aristotle to study hundreds of Google’s teams and figure out how to build a perfect team. The results turned out surprising: personality types, skills or backgrounds made no difference, whereas “conversational turn-taking’’ and ‘‘average social sensitivity’’ as aspects of psychological safety were the determinants (Duhigg, 2016).

Based on this, the present report attempts to design and build a system prototype to improve team’s psychological safety environment by raising group member’s social sensitivity, thereby enhancing group performance.

Context

Theoretical Context

1. The definition of social sensitivity

Social sensitivity is the personal ability to perceive, understand, and respect the feelings and viewpoints of others generally on a nonverbal level (Bender et al., 2012). This capability enables people read others’ emotions and moods through facial expressions or body languages. Salovey and Mayer describe social sensitivity as skillful recognition of others’ emotional reactions and empathic responses to them and view social sensitivity as an element of emotional intelligence (Salovey and Mayer, 1990) (MERSINO, 2013) (see Figure 1).

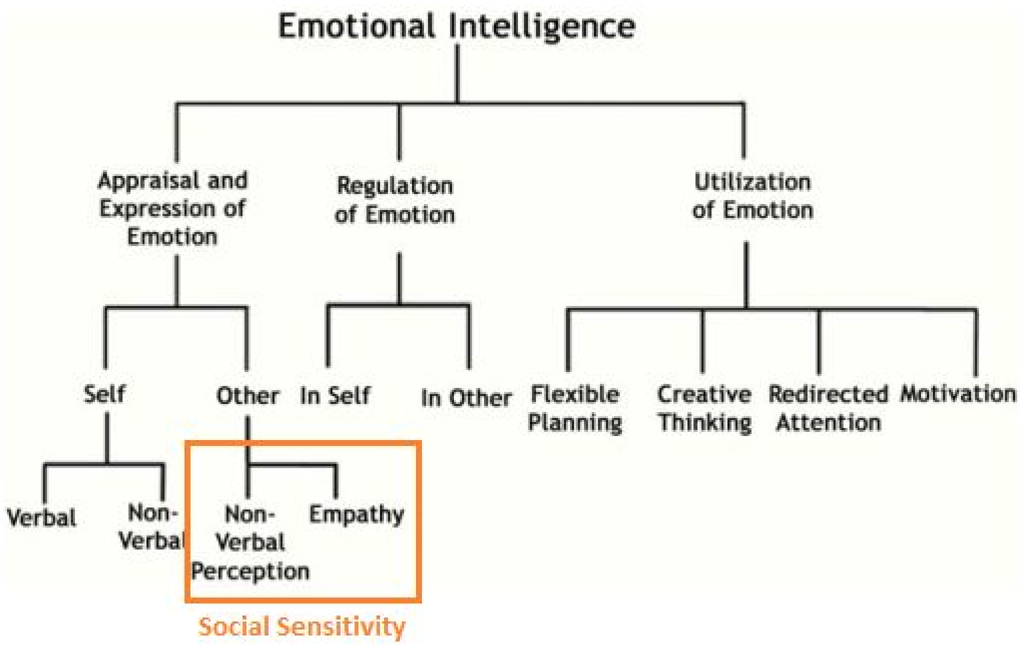


Figure 1: Salovey and Mayer Framework for Emotional Intelligence

2. The importance of social sensitivity to group effectiveness

It has been proved in some researches and experiments that social sensitivity of a team is significantly correlated with successful team performance (Bender et al., 2012)(Cooke et al., 2015). Teams with higher average social sensitivity level tend to perform better in various tasks. Social sensitivity, rather than individual intelligence and personality, is the most important factor in raising the overall group intelligence which contributes to team effectiveness (Frankel, 2010; Cooke et al., 2015).

Since social sensitivity is the ability to perceive emotions through nonverbal expressions, it leads to smooth interactions and communication between team members. People in this environment experience higher emotional satisfaction and lower psychological pressure, which aids in innovative thinking and problem solving.

Moreover, social sensitivity as part of psychological safety (Duhigg, 2016) is also beneficial to building positive group norms. Psychological safety is defined as a shared belief that the team is safe for interpersonal risk taking, which in turn encourages people to be more confident in contributing to the team. This confidence stems from mutual respect and trust among team members (Edmondson, 1999) and helps to form a team climate to enable the willingness to contribute to collective work (Kramer, 2004).

3. Gauging social sensitivity

Social sensitivity is measurable in some ways.

1) Reading the Mind in the Eyes test

The revised version of ”Reading the Mind in the Eyes” test, created by the Cambridge psychologist Simon Baron-Cohen (Baron-Cohen et al., 2001), consists of 36 cropped grayscale photos, focused on the area around eyes, to loosely measure the ability to recognize other people’s emotion. When doing the test, participants should choose one of four words to best describe the photo as quick as possible. The minimum score is 0, the maximum 36, and the average 26.2. Compared to the original 1997 version, which has only 25 photos and 2 choices for each photo, the new version is more balanced in terms of the number of male and female photos and offers subtly similar options to increase the difficulty level, thus improving the accuracy of the result. Because of its high reliability, this test is used in both fields of neuroimaging and lesion studies and is broadly used to measure social sensitivity.

2) George Washington Social Intelligence Test (Kihlstrom and Cantor, 2000)
The GWSIT (Hunt, 1928; Moss, 1931; Moss, Hunt, Omwake, & Ronning, 1927; for later editions, see Moss, Hunt, & Omwake, 1949; Moss, Hunt, Omwake, & Woodward, 1955) was composed of a number of subtests, which can be combined to yield an aggregate score. The subtests include Judgment in Social Situations, Memory for Names and Faces, Observation of Human Behavior, Recognition of the Mental States Behind Words and Sense of Humor. The test is usually used to assess social intelligence which means the ability to deal with people (Hunt, 1928), so it contains social sensitivity part, but covers much wider aspects.

Technical Context

1. Measuring Emotions

1) Electroencephalogram (EEG)

Figure 2: 14-channel Emotive EPOC by Emotiv Inc.

Ramirez et. al. use Emotiv Epoc to capture the EEG signals, particularly alpha (8-12Hz) and beta (12-30Hz) and use machine learning techniques to classify the emotions (Ramirez and Vamvakousis, 2012). However, distinct from the previous studies which validated the results using the participants’ subjective judgement, they use emotion-annotated music from the International Affective Digital Sounds, University of Florida, to train the system. The analysis used two two-class classifiers, based on valence (positive & negative) and arousal (low & high).

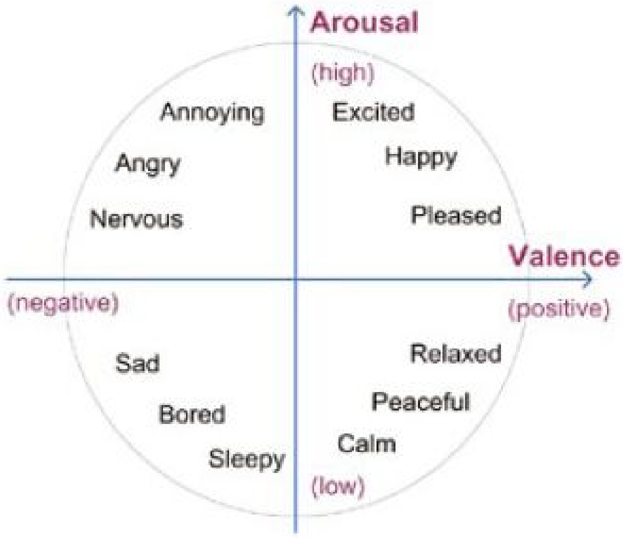


Figure 3: Emotional state in the valence/arousal plane

The level of arousal (excited vs calm) is inferred by the ratio of beta and alpha signals. Beta waves are associated with high brain activity, whereas alpha waves with inactivation.

Based on the argument that affective valence is related to directions towards the stimulus, they observe two cortical hemispheres—left frontal and right frontal, to determine valence. Left frontal inactivation is associated with withdrawal—thus indicates negative valence, while the right frontal inactivation indicates thus positive.

2) Heartbeat

We observed several studies that utilise heartbeat to approximate human's emotional state. Wiens et. al. (Wiens et. al., 2000), found that heartbeat is correlated to the intensity of emotional state, but not with valence. A higher rate indicates stronger emotion, which can be either positive (e.g. amused) or negative (angry or fear). (Wiens, Mezzacappa, and Katkin, 2000)

Using a slightly different approach, Valenza et. al. (Valenza et. al., 2013) utilise heart rate variability (RR), induced by short-term (<10 seconds) stimuli, to approximate emotional states, represented by the Russel's circumplex model, in real time. They managed to present sufficiently good classification accuracy of valence. (Valenza, 2013)

Using a more advanced and non intrusive approach, Katabi et. al. from MIT's Computer Science and Artificial Intelligence Laboratory (CSAIL) measured emotional states from segmentation of heartbeat, collected wirelessly using EQ-Radio. The system works sufficiently well on classifying 4 states derived from the arousal-valence model: Joy, Pleasure, Sadness, Anger. (Zhao, Adib, and Katabi, 2016)

Research

Models of emotion

Emotions are complicated and difficult to categorize, so researchers have built a number of models of emotions for analysis. For both theoretical and practical reasons, they define emotions based on one or more dimensions (*Emotion classification*, 2016). One of the most prominent dimensional models is James Russell's circumplex model (Posner, Russell, and Peterson, 2005).

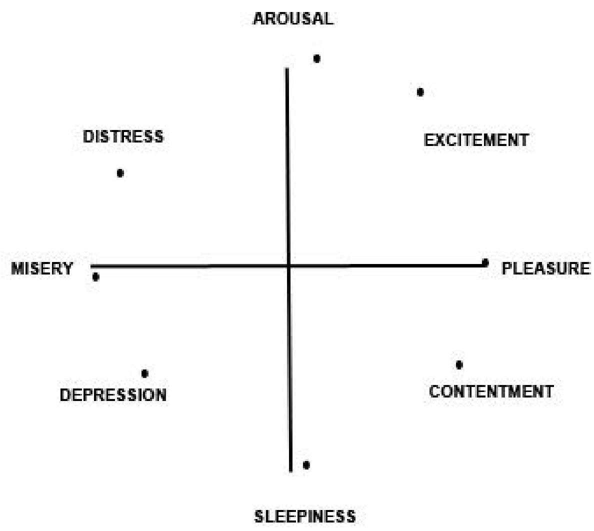


Figure 4: Circumplex Model of Emotions (James Russell 1980)

This model describes emotions in a two-dimensional space. The vertical (north-south) axis shows the degree of arousal – the closer to the north means more activated. While the horizontal (west-east) one implies happiness level – the closer to the right means more pleasant. In this way, the whole space is divided into four quadrants and other emotions like angry and sad will be scattered in this coordinate axes based on their respective values on horizontal and vertical dimension. Depression, for example, can be defined precisely as falling at a point in the southwest, the combination of low arousal and pleasure and its bipolar opposite is excitement. Through tests and analysis, 28 kinds of emotions were plotted in this coordination axes (shown in Figure 3) (Posner, Russell, and Peterson, 2005).

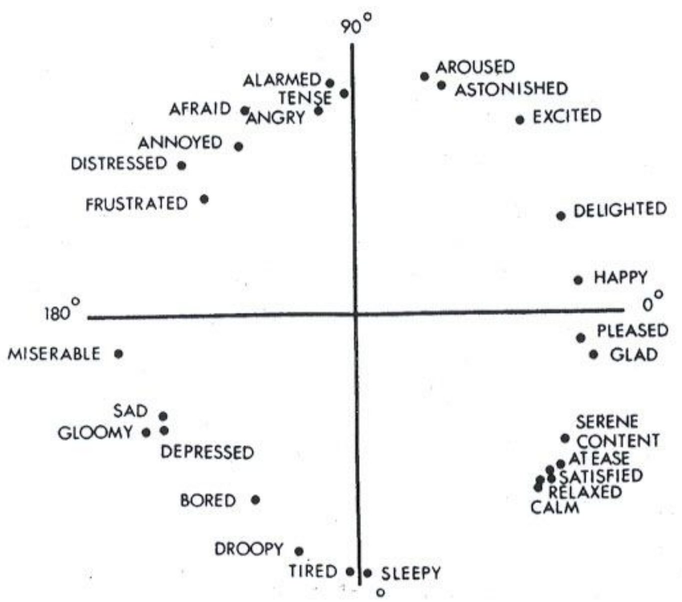


Figure 5: 28 emotion words in Russell's model

Psychological Property of Colour

Colour is nature's own powerful, signalling system - the universal, nonverbal language. It is commonly associated with emotions, whether it has a direct impact to emotional state, or as a representation of certain emotions (Hemphil, 1996; Mahnke, 1996). There are numerous researches about colour interpretations, in which they mainly emphasise on the different meanings for each colour, following the innate, cultural, and personal background (Njidam, 2009). Hence, it is quite difficult to abstract each colour to the most intense emotional meaning. As seen on figure 1, colours are divided into list of attributes of traits and the most common emotion meaning (Njidam, 2009).

Color	Positive trait	Negative trait	Emotion
Red	active, emotional	offensive, embarrassed	anger, love
Orange	ambition	tiring	joy, determination
Yellow	lively, energetic	cautious	fear, Happiness/joy
Green	calm, neutral	greedy, sick	faith, greed
Blue	faithful, traditional	depressed	confident, sadness
Purple	leadership, passive	arrogant, sorrow	introspective, melancholic

Figure 6. Claudia Cortes Colour Extraction

However, the usage of colour in a technology products has been significantly increased, whether it might give a meaning of the certain state of a system, or a symbol of a response to an interaction (Hüllermeier et al, 2010). The most basic colours that has been commonly used in almost every visual contexts especially in electronic system are RGB, in which Yan

Xue distribute those colours into emotional interpretation by using Russels Circumflex model as the basis (Njidam, 2009).

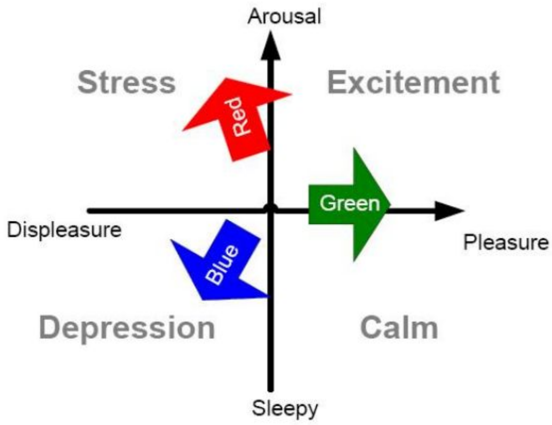


Figure 7. Yan Xue Colour Distribution

User Research: Reading the Mind in the Eyes Test

To test for the average level of people's sensitivity, we did a survey asking people to do this test and record their scores. The results show that the scores range from 15 to 33, with the average of 24. Considering the low average score, which is approximately half of the full marks, our hypothesis has been corroborated: it is difficult for most people to perceive others' emotions only from external expression. Thus, it is necessary to find a way to help individuals improve their social sensitivity.

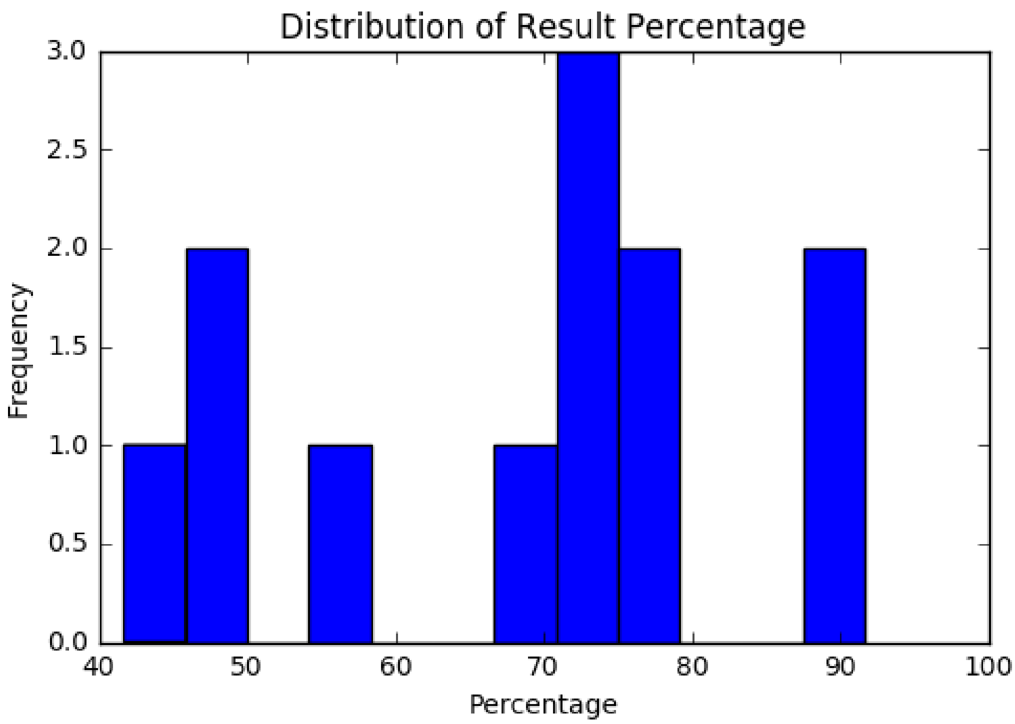


Figure 8: Distribution of the Results

Design Methodology

Generally we draw from British Design Council's Double Diamond approach (British Design Council, 2005) and revamp it to suit our project better (see figure 9). In the 'discover' phase, we explored topics through personal experience and psychological literatures. Following this, psychological knowledgement and biophysical factor measurement methods such as EEG and heart rate were investigated. Based on tests and research, insights were gathered and the area was determined to focus on. Through brainstorm ideas were proposed, discussed and prototyped. By data collection and visualization the system was evaluated and optimized as well the final proposal was put forward.

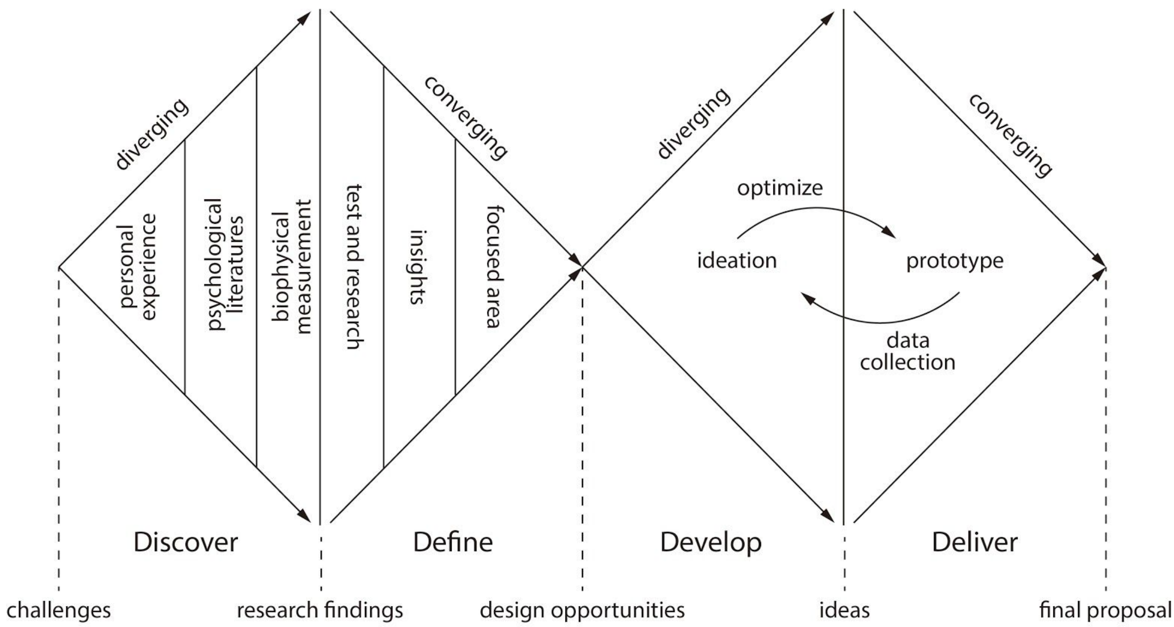


Figure 9: Double Diamond Design Process

Proposed System

System overview

Based on the research above, we decided to design an assistive system seeking to help group members improve their social sensitivity in the setting of a group discussion. Considering the result of our initial survey that most people have trouble detecting others' emotion, and supported by Bailenson et. al. research that machines, are algorithmically better at inferring emotion than humans (Bailenson et al., 2008), we choose to utilise machine learning techniques to infer group members' emotions. The resulting readings are then aggregated and broadcasted back to the group. In addition to the real time emotion detection and display, it is possible to retrieve the data in the format of emotion-annotated meeting minutes for further analysis.

The real time components consist of the data collector headset, connected wirelessly to the server. The headset collects three types of data: EEG and heartbeat for determining emotion, and voice that fed to the ASR to produce the meeting minute.

In general, the system has two main functions: detecting emotions and reviewing recordings. It translates the data collected by the headset into emotions it represents and display the average activation and pleasure level on our device in real time. Besides, the voice recorder converts words into texts and records the corresponding emotions for reviewing.

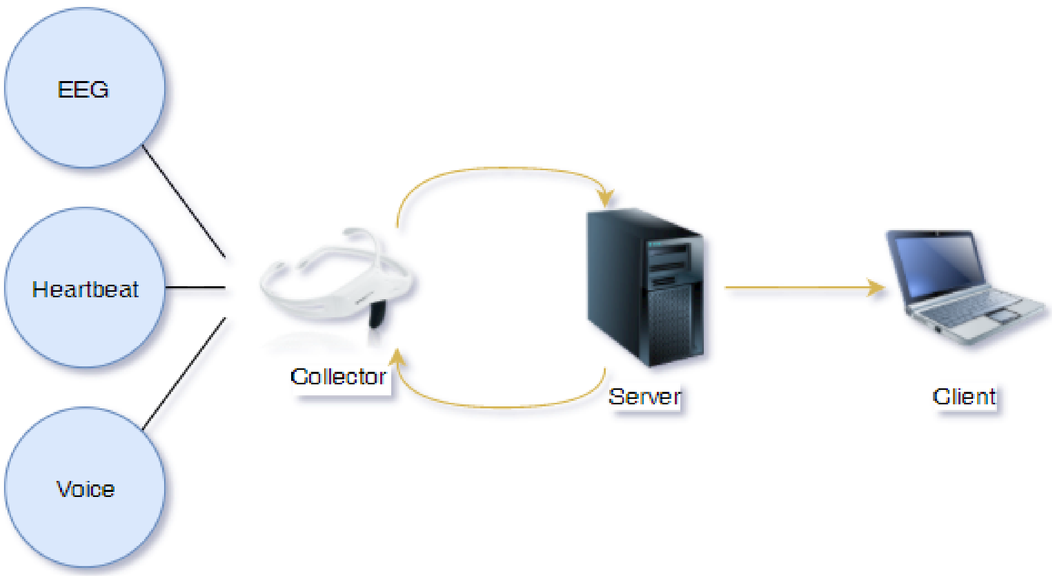


Figure 10: System Architecture

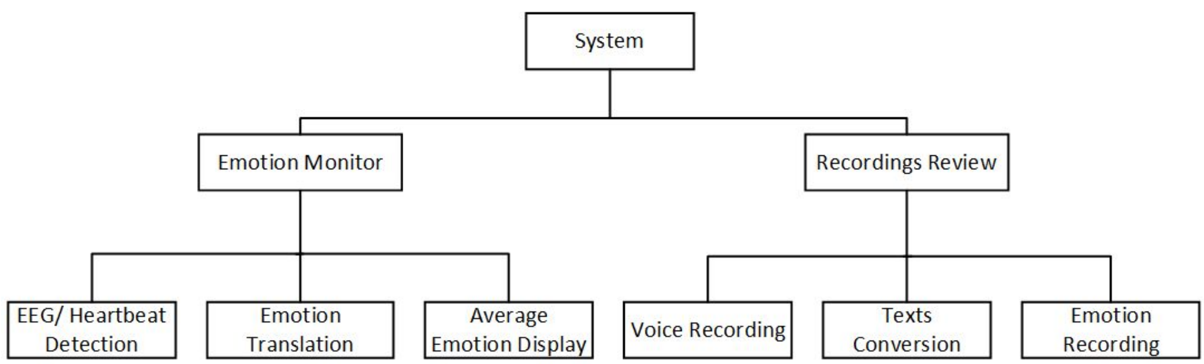


Figure 11: Functional architecture diagram

The system workflows for these two functional parts are as followed:

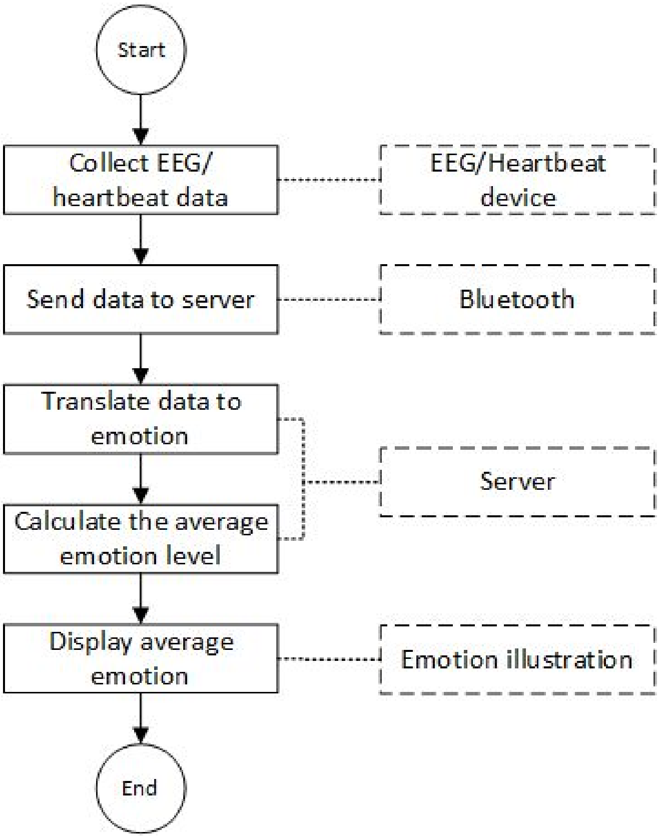


Figure 12: Emotion monitor workflow diagram

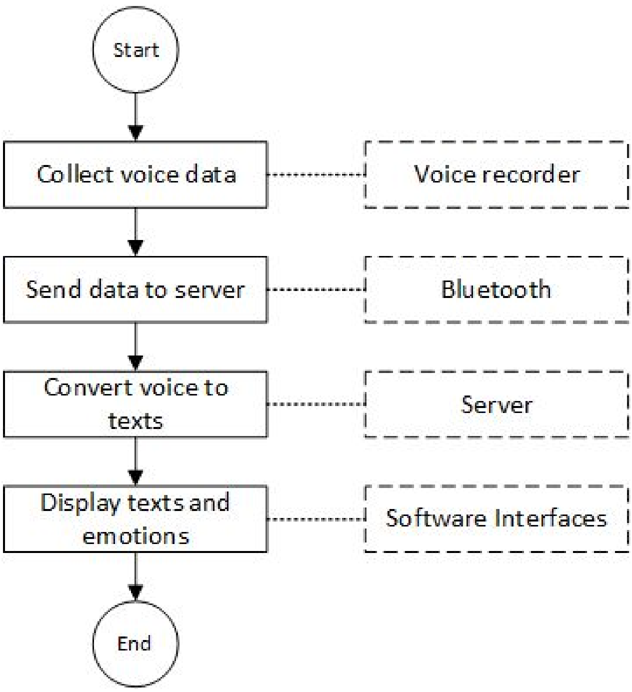


Figure 13: Voice recorder workflow diagram

1. Headset

The headset comprises two functions: 1) collecting data, and 2) displaying a representation of the average emotion. It collects each individual's EEG signal, heart rate, and records voice. EEG and heart rate are fed into the the emotion translation module to infer emotion, while the recorded voice is fed into the automatic speech recognition module.

It also displays average emotion-state of the group as a line of color. The colours represent the average level of pleasure. Blue means very low level of pleasure. On the contrary, orange is very high level of pleasure. The length of the colour bar represents the average level of activation. Short bar means low level of activation while long bar means high level.

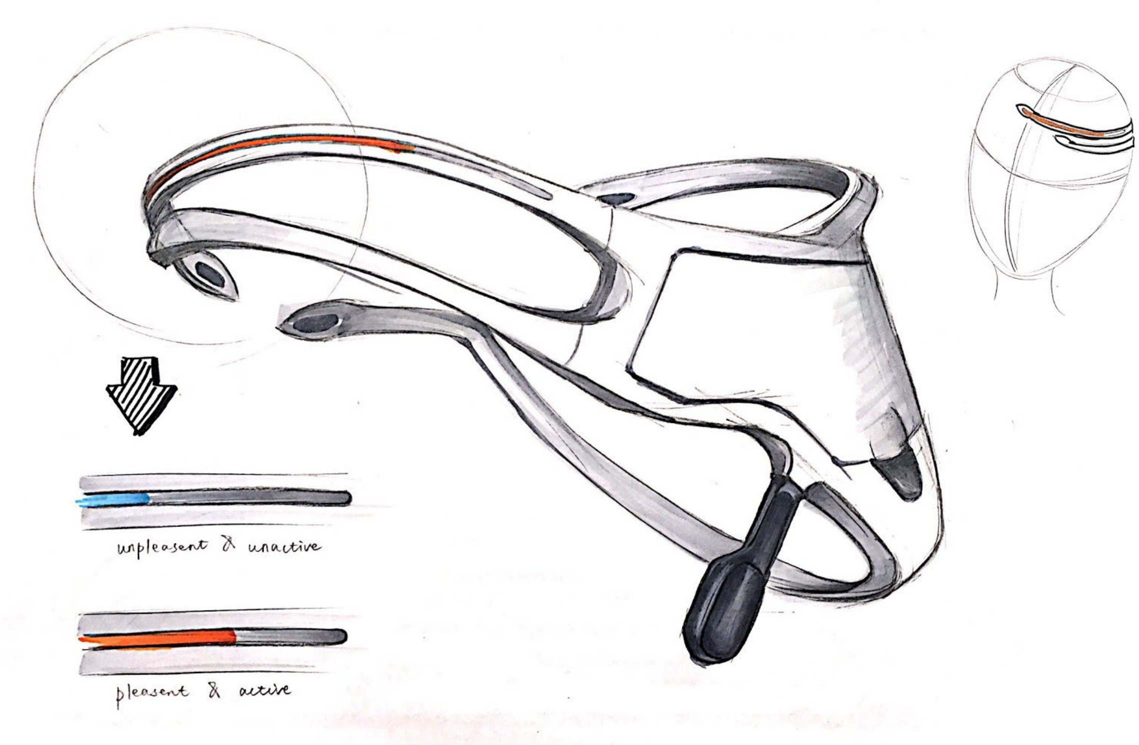


Figure 14: Data collector and explanation

2. Post-Discussion Analysis Software

After the discussion, the data on the server is available for more analysis and review. While the possible use for this data is unlimited, we are interested in presenting emotion-annotated minutes. The average emotional states are embedded into the ASR constructed meeting minute. This document is then available to all group members for further review and analysis.

This format can help groups review their meeting, identify essential parts, and make decisions. They can also learn to plan a more effective and efficient meeting by studying the previous emotion-imbued meeting minutes.

The software is an add-on for word editing software, specifically designed for Google Docs, knowing that it has a sharing feature that facilitates users to collaborate in a real-time environment, Google Docs has been used as the most convenient and common tool for doing a group project, especially for writing tasks. The software works as a visualiser of emotion data gathered from the hardware as well as the activities—discussion with a voice recorder that has been converted into texts—occurred in that time, which then, will display the average emotions among all group members. Also, it enables users to record the emotion and texts data that can generate an output as a document that shows emotion-annotated meeting minutes that can be reviewed after meeting as a group evaluation.

- Interface

  For the interface, we follow the default google docs interface rules for add-ons, in which we could not change nor put any complex interface within the system, thus adding a sidebar as to show the function of the software.

  In the start page (figure 15), there is a function to connect to the headset. Before user connect the hardware, the emotion annotation minute option could not be operated.

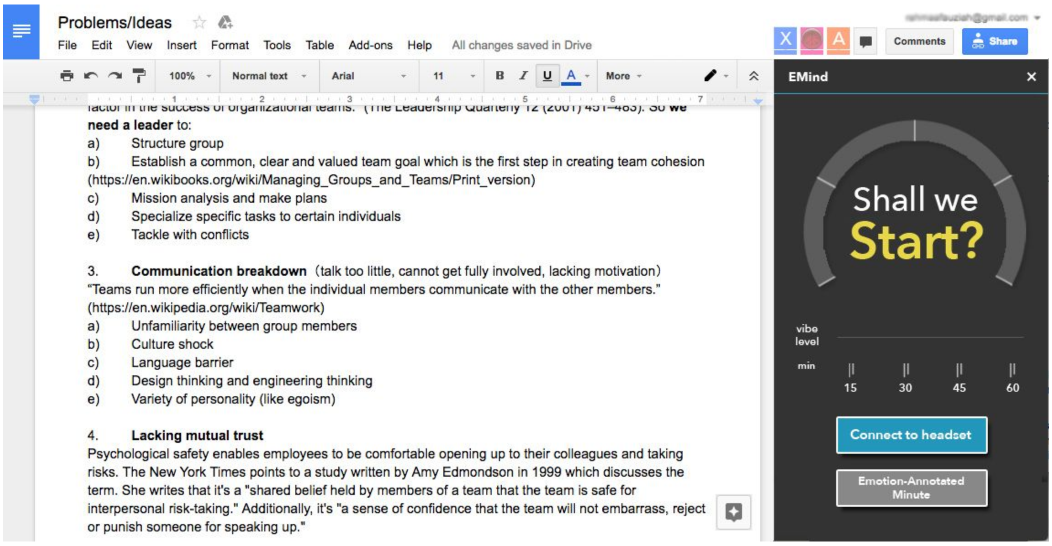


Figure 15: The start page of the add-on software

  After the hardware connected to the software (figure 16), it shows the summary of the average mood among all the group members as well as the graph that display the mood changes in a specific timeframe when the discussion occurred. Also, user can access the data of detailed interaction, such as the graph that display the mood progress throughout the discussion in a form of Emotion-Annotated Minute (figure 17), which has a specific template to showcase the data, including the texts from the converted voice in a certain time stamp as well as its mood level based on data collector's interpretation. The data will be appeared as a separate google docs and user will be redirected to that page once they clicked on the Emotion Annotated Meeting button.

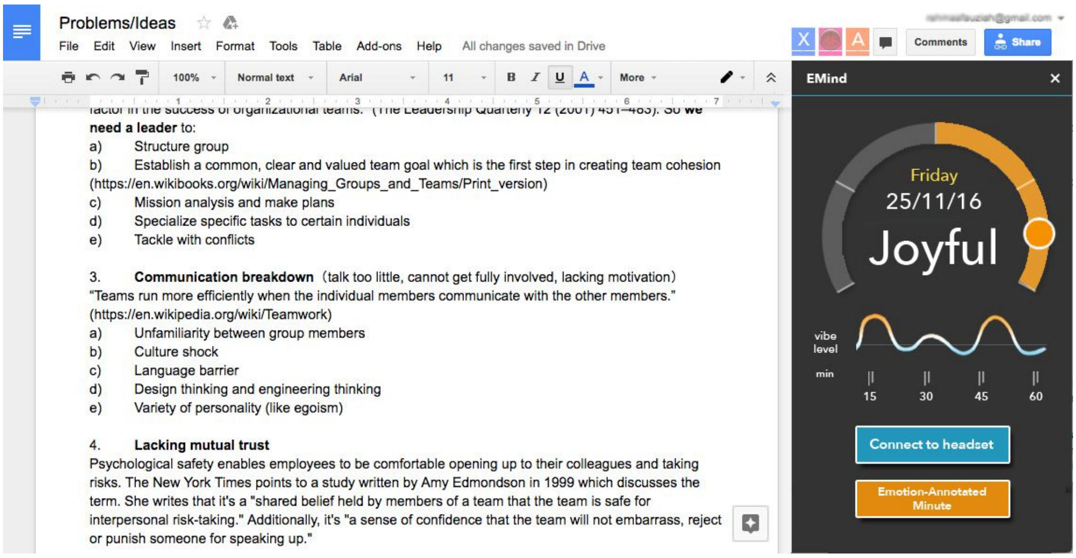


Figure 16: interface of the software after it connects to the hardware.

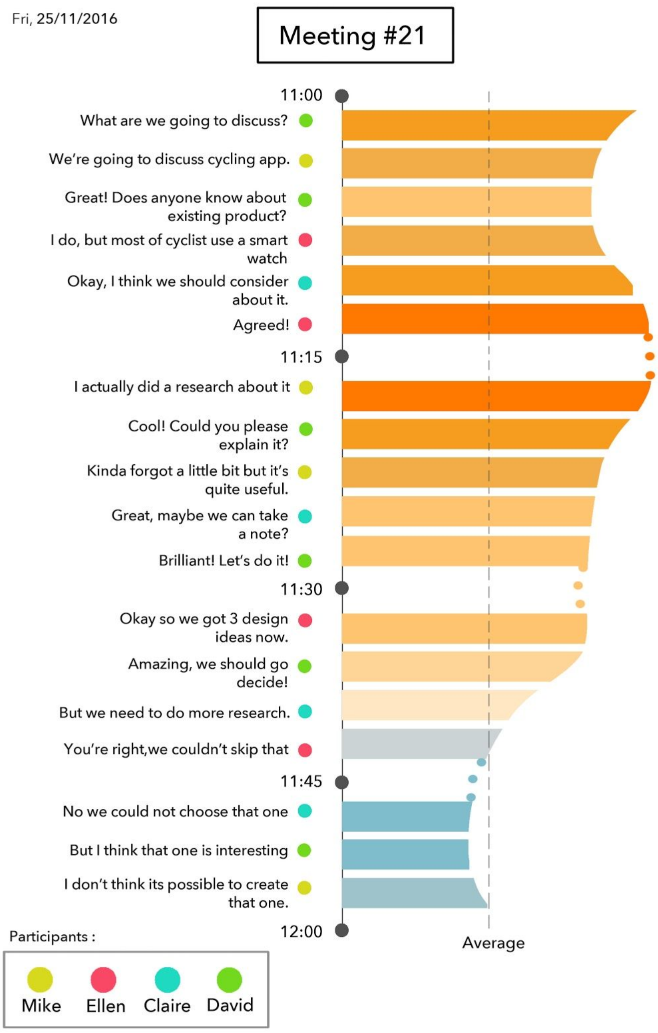


Figure 17: Emotion Annotated minute

Use Case

1. Use Case

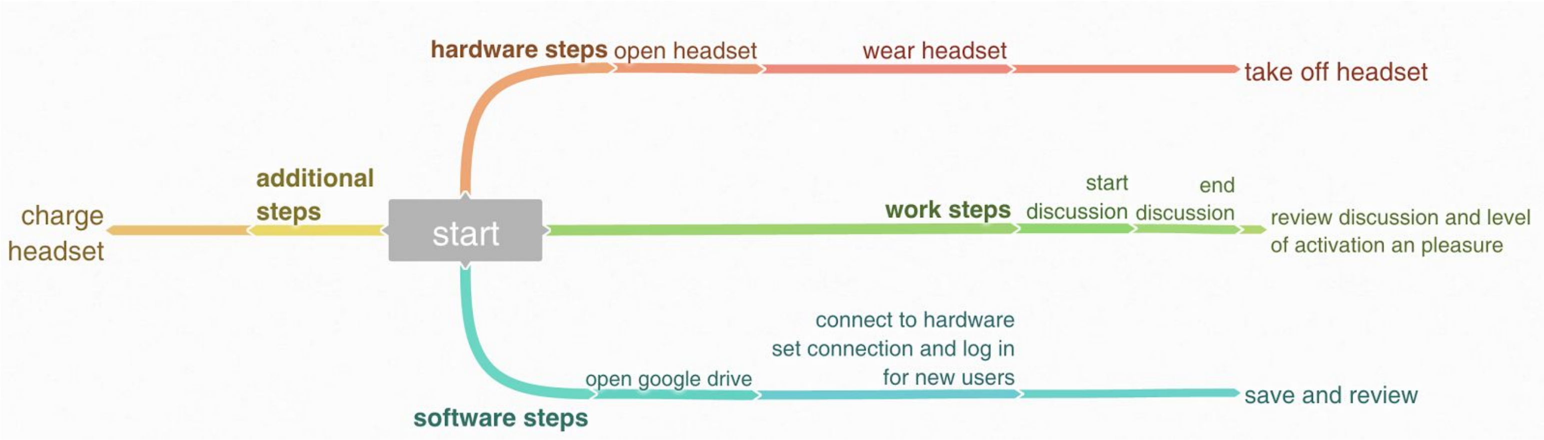


Figure 18: Use case

2. Sample Scenario

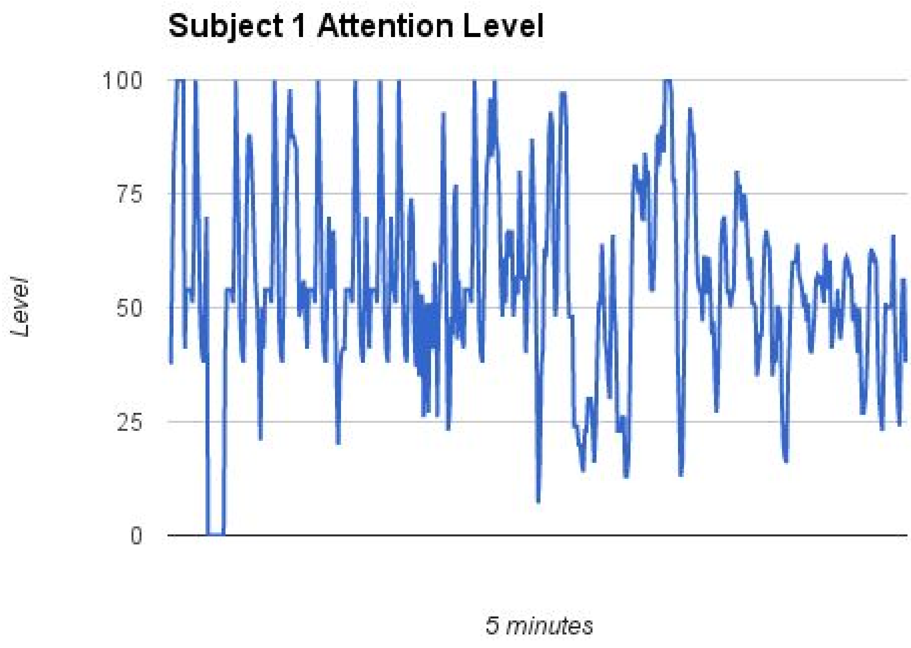
A group of 4 teammates are working on assignment 3 of Case Study. They are A, B, C and D. Today is their third discussion and everyone is supposed to finished the tasks set on the second discussion. After they gather together in Design Informatics room around a square table, everyone picks up the headset, open and wear it. A opens his computer and enters Google Drive that has been shared with all team members. Then everyone's headset is connected to the Google Drive document automatically because in the first time every headset has been connected to the document. When they start discussion, B talks about her tasks that is writing research part for the paper and brings up some questions in other part of the paper. The headset senses her activation is high and shows the average level of activation in the group is high. The software that has been linked to the document records B's voice and transfers it into words as well as records the level of activation and pleasure of the team. After 2 hours of discussion, the emotion illustrator shows the average level of activation going down which means team members may get tired. Then C goes to bring some drink and snack to share. The average level of pleasure shown on the headset turns from light orange into red orange, which means the happiness level goes up. After half an hour, they finish discussion and turn off the headsets. D is confused about the last part of the discussion and he reviews the discussion on Google Drive document and listens to the record.

Evaluation

Input Data

Input data consists of EEG brainwaves, heartbeat, and voice. In the scope of emotion detection, we present sample EEG and heart rate data. While this raw data is stored in the server, their main use is to infer emotional states, and in turn create visualisation of the average emotion of the group.

1) EEG



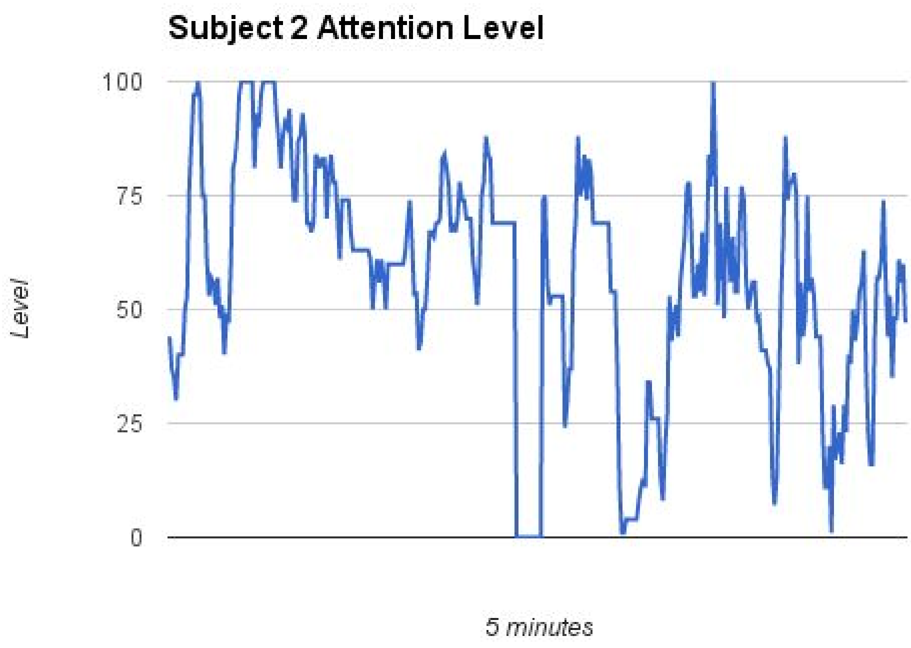
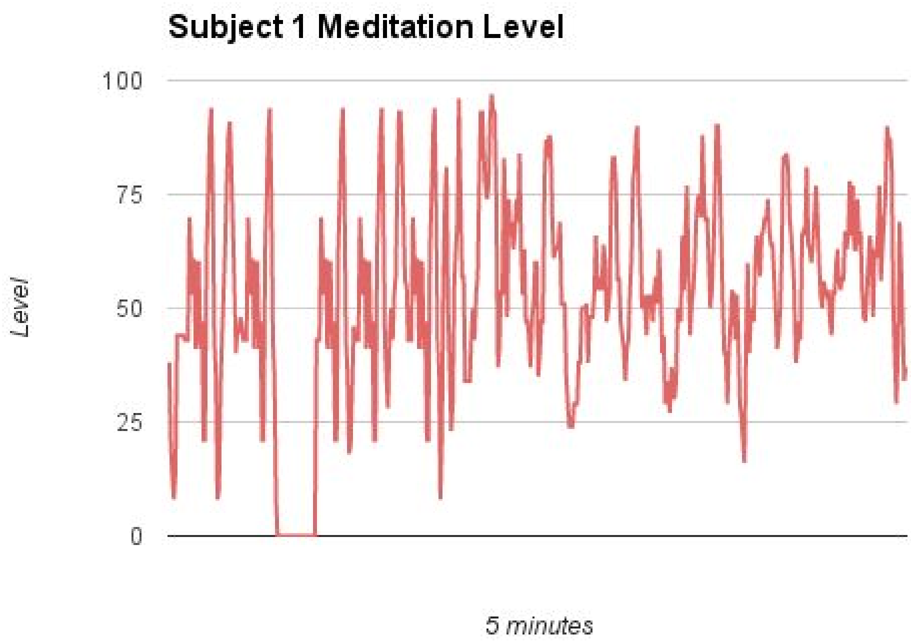


Figure 19: Subjects 1 & 2's Attention Level over 5 minutes



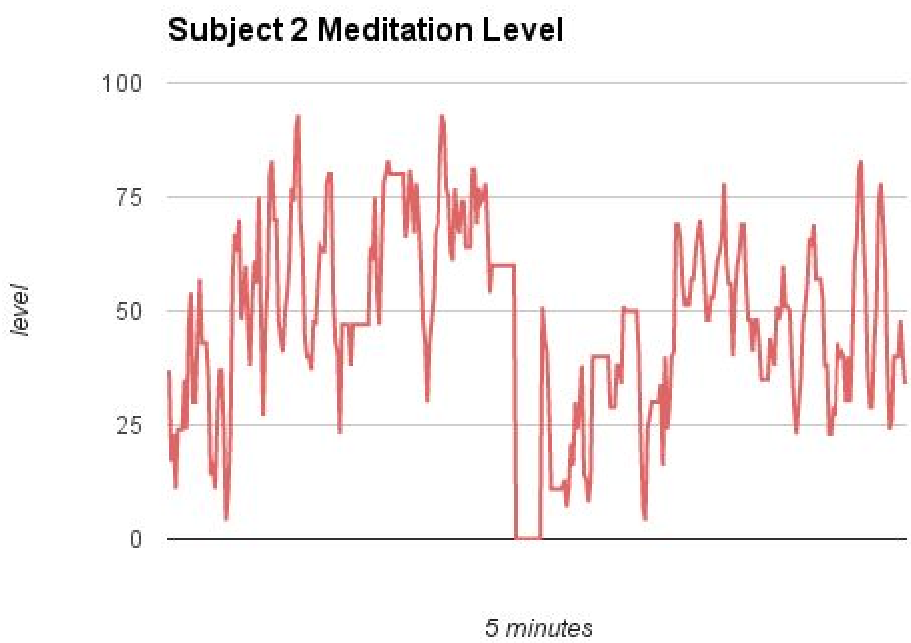
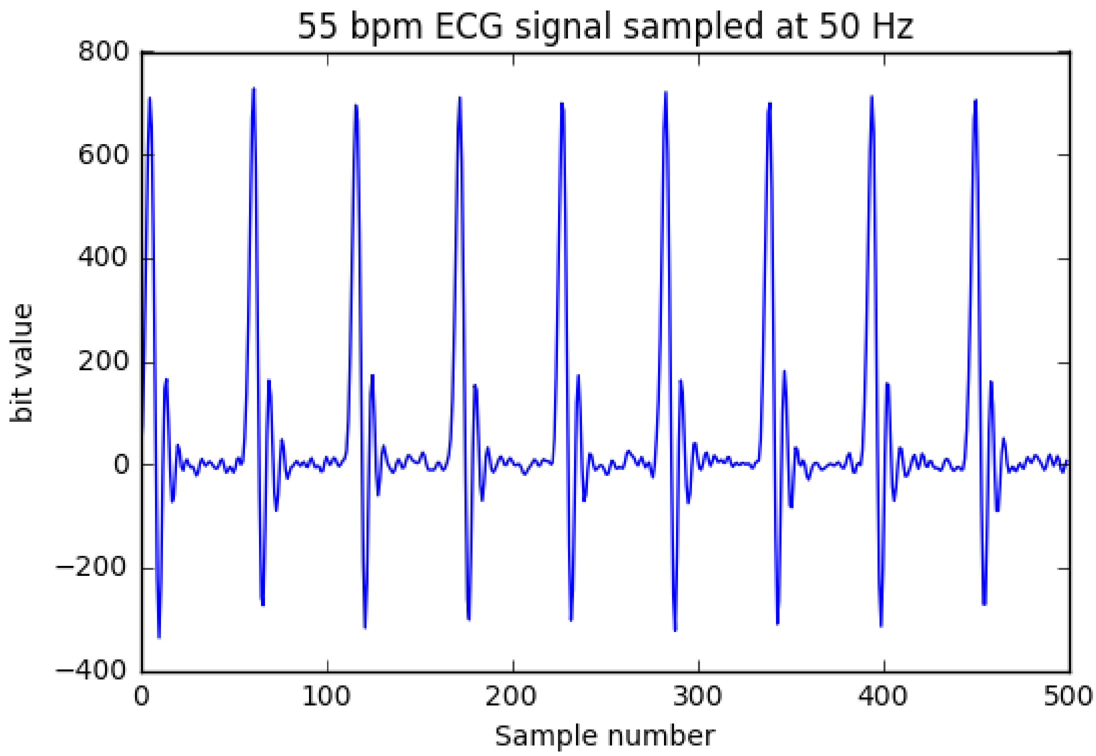


Figure 20: Subject 1 & 2's Attention Level over 5 minutes

2) Heartbeat



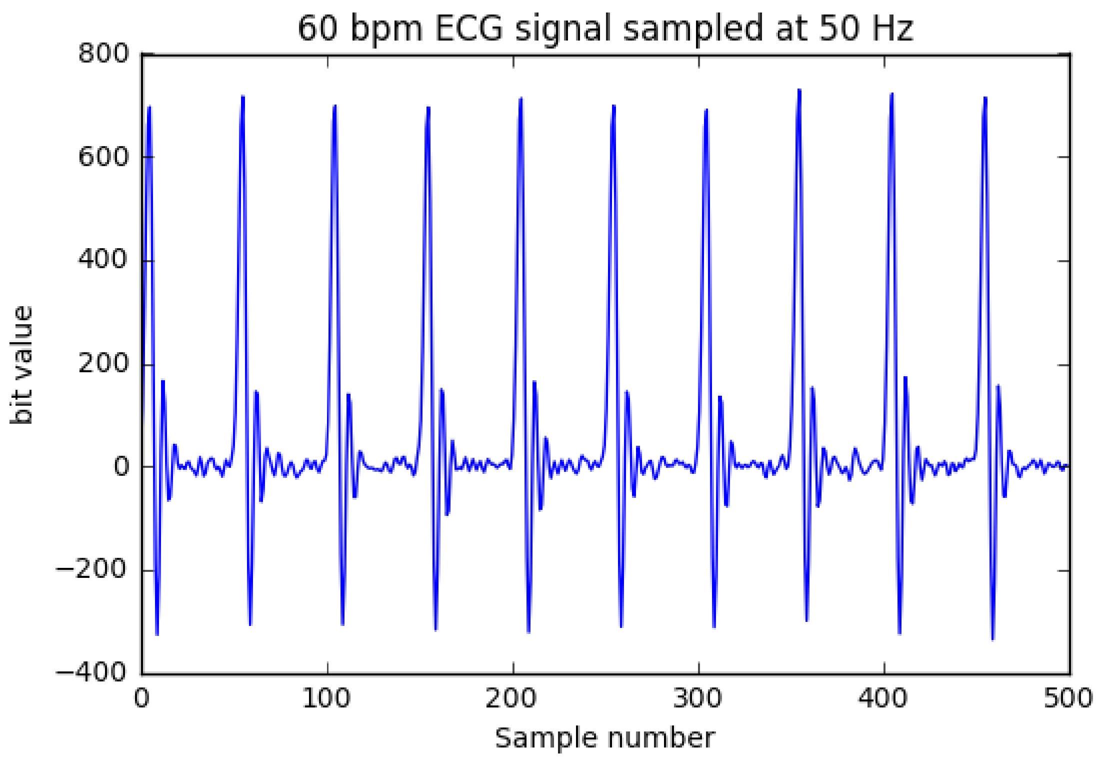


Figure 21: Subject 1 & 2 Heart rate samples

Output Data

This visualisation is available in real-time to all the group members attending the group discussion. We considered another option of displaying this only to the member who is actioning, but in group discussions controls are transferred very quickly, thus it is hard and possibly inconvenient to the users as well to implement such mechanism.

The secondary output is the emotion-annotated meeting minutes mentioned above. This document is available on demand to the group members as reviews and an analytical tool of their previous meetings and planning next ones.

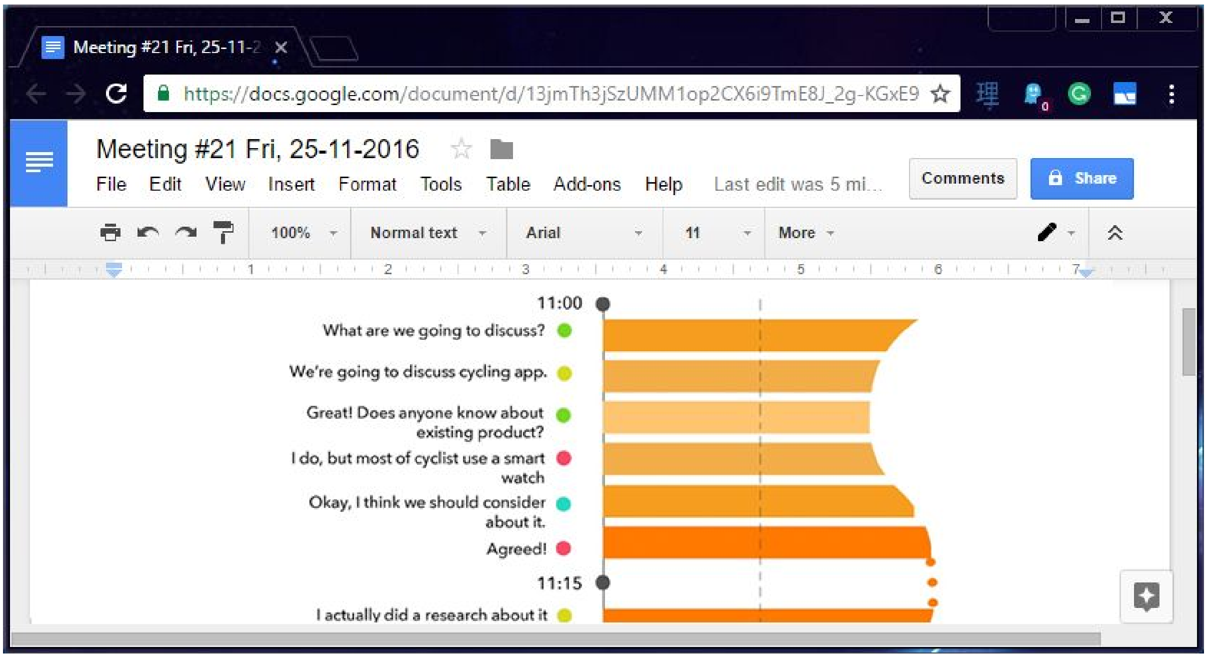


Figure 22: Emotion-Annotated Minute

Lastly, serving as a research tool, anonymised data on the server is available for mining by researchers. The data must go through a separate anonymisation process that strips all identifying attributes from the it.

Related groups using the system must give their consent beforehand that the data generated from their activities might be used in other research, given that it is completely anonymised. Researchers and the groups must also agree on the type of data transferrable. For instance, non-identifiable EEG and heart rate readings may be retrieved freely, but not the recorded voice nor the minute scripts.

Discussion

We imagine that at first group will need some time to be used to color cues on the device. Then we believe that individuals will be more sensitive to the atmosphere of the group discussion. Groups will likely come to a consensus as to what reading they would define as the optimum sentiment, and consequently will try to achieve and maintain this collectively.

In terms of limitations, there are several possible problems that may arise. First of all, there might be a limit to how long average people can wear the device comfortably. One possible solution is to design a more ergonomic headset that people can wear significantly longer.

Another possible solution is completely abandon EEG and favor for metrics that allow less intrusive mechanism yet with paralleled accuracy of inferring emotion. The other issue worth more investigation is what negative effects the system may have to both the individuals and the team as a whole. For example, a group member might feel discouraged when he noticed a negative slope in the group's average sentiment in relation to what he/she was doing. Other members might unconsciously alter their perception to what the system displayed; they might accuse him of worsening the average mood. Viable solutions to this will need more investigation.

We are also interested in the possibility of minimising or erasing altogether anonymity in favor for more natural interactions. In such version, the headset reading will tell each individual's emotional state as opposed to the group's average, since arguably, this what actually happens in traditional interaction; emotion assessments are in personal basis.

Lastly, there are two other scopes that we are interested in as well, but not covered in this document: 1) assisting individuals at building permanent social sensitivity, and 2) taking into account the fact that in the real world, individuals can be members of multiple equally cognitive-demanding and labour-intensive commitments; either other group or individual projects.

Reflection

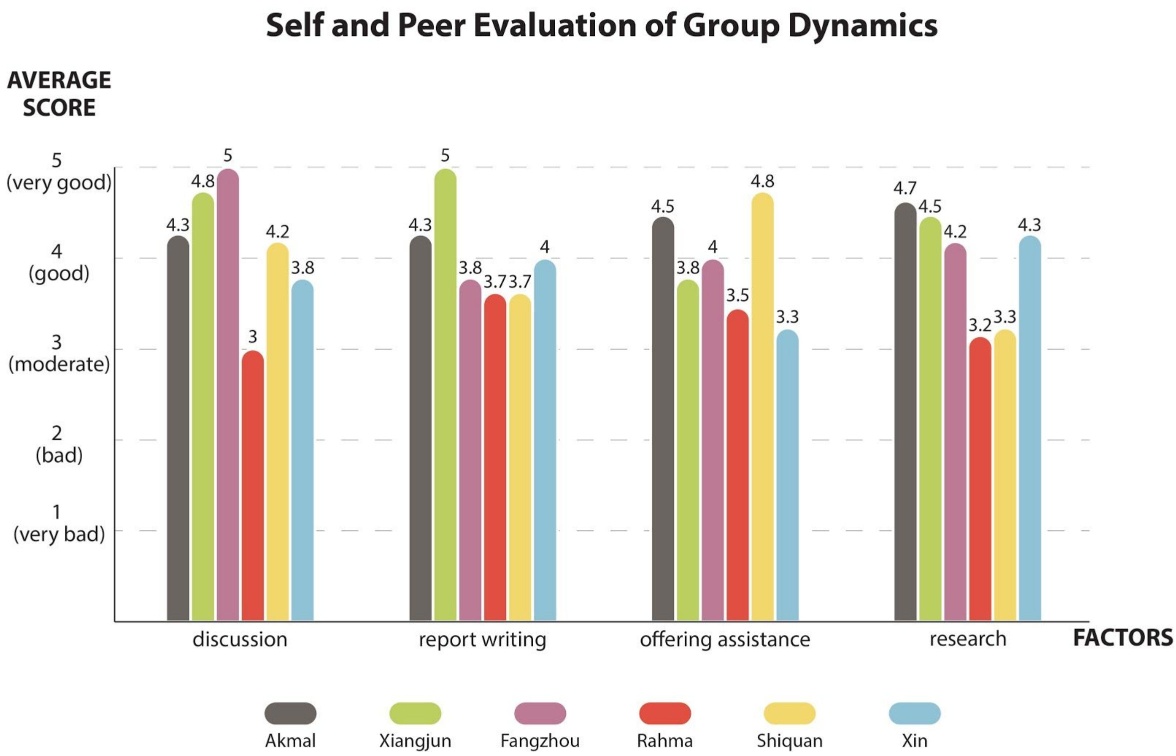


Figure 23: Self assessment results

We have developed a crude metrics to rate our group members' individual contribution. After some discussion, we decided that the top four aspects deemed most essential in our group work are as follow:

a. Contribution in discussion. We held a couple of team meetings throughout the course of the project. Here we are looking at presence, contribution on ideas, and the ability to conform to decisions made.

b. Contribution in report. This can be writing, producing of graphics, and other tasks related to the development of the final report.

c. Offering assistance. In other words, being initiative.

d. Contribution in research. This includes how relevant the research to the topic of discussion as well as the amount of useful information extractable.

Each member then score themselves and others.

As shown in the figure 23, everyone's performance fluctuates in different factors. Fangzhou and Xiangjun get full marks in discussion and report writing respectively, though both of their lowest scores are 3.8, in report writing and offering assistance for each. When focus on different members' performance in the same factor, the most obvious gap is in discussion, from 5 to 3, which is also the lowest score in all factors.

If we had more time, we would like to give weights to these factors, possibly in different combination for every member. For instance Member 1 will have such weighing {discussion: 3, report: 2, initiative: 2, research: 2}, but another can have {2, 3, 3, 2} for the same respective aspects. This is because we realise that everyone's strong points and likings are diverse. In addition, members have varying circumstances that limit them in contributing in similar ways with the others.

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