Chapter 1: Introduction

Cyberpsychology research has been greatly improved by recent developments in sensor technology, especially non-invasive sensors like heart rate variability (HRV) monitors and eye-tracking devices (Ancis, 2020; Trigona et al., 2020). These technologies make it possible to precise observation and measurement of human behavior, including physiological data into psychological assessments (Caponnetto & Milazzo, 2019). Even with these advancements in technology, there is still a significant lack of information in the literature about thorough multimodal techniques in psychophysiology (Baig & Kavakli, 2019; Patrick et al., 2019).

According to Donnelly et al. (2023), HRV is acknowledged as a reliable biomarker for the autonomic nervous system that can represent both physiological and psychological states. Nonetheless, the current body of research in cyberpsychology reveals underdeveloped objective assessments of anxiety (Senaratne et al., 2021). Existing studies that compare physiological data with self-report measures often suffer from methodological weaknesses and limited sensor integration (Hickey et al., 2021; Alrefaei et al., 2023). Moreover, few studies utilize comprehensive multi-sensor measures, leading to confounded predictive features (Pizzoli et al., 2021).

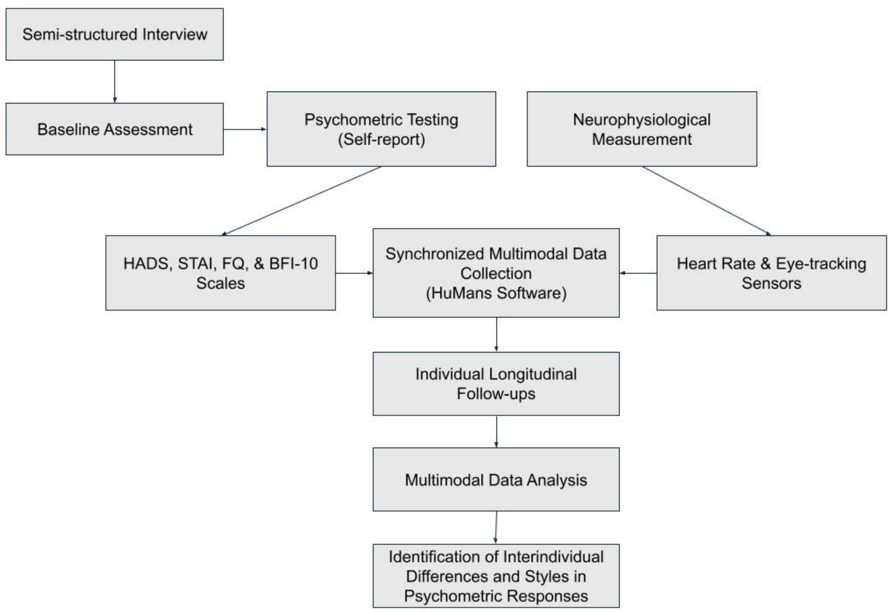
This study seeks to address these limitations by evaluating whether a unique multi-sensor and multimodal protocol can effectively assess anxiety and depression. Integrating neurophysiological data into psychometric testing offers the potential to transform our understanding of cognitive and emotional processes. Traditional psychometric methods predominantly rely on mostly self-reported data and performance outcomes, often overlooking subtle physiological responses during cognitive tasks.

Our research employs a longitudinal design to explore the neurophysiological reactions among young adults during psychometric testing. We will correlate self-reported data from instruments such as the Hospital Anxiety and Depression Scale (HADS), State-Trait Anxiety Inventory (STAI-State), and Fear Questionnaire (FQ) subscale for anxiety and depression with neurophysiological measures. Control psychometric measures will include the 10-item Big Five Inventory (BFI-10), STAI-Trait, and FQ Phobia scales. High-quality sensors, including eye-tracking devices and HRV monitors, will capture detailed physiological responses during cognitive Performance.

The primary goals of this research are to determine whether neurophysiological indicators are linked to particular cognitive and affective states, look into individual variations in these markers, and assess the viability and usefulness of multimodal, multisensory techniques in psychometric studies. By analyzing these data, this research seeks to provide a more thorough and precise technique for evaluating anxiety and depression. This work aims to improve our comprehension of the complex interactions between physiological and psychological states by combining cutting-edge sensor technologies with psychological testing.

Chapter 2: Methodology

The methodology of this study integrates both qualitative and quantitative approaches, using semi-structured interviews, psychometric testing, and synchronized multimodal data collection with advanced software and sensor technologies. The process is meticulously designed to gather comprehensive data on participants' both psychological and physiological states.



Semi-structured Interview

The study began with a semi-structured interview conducted with each participant. This interview’s purpose is to gather qualitative data and initial insights into the participants' psychological states and baseline characteristics. Through open-ended questions, the interviewer collected detailed background information, demographic information, and context relevant to the psychometric assessments.

Baseline Assessment

Following the interviews, a comprehensive baseline assessment was performed to establish a reference point for the participants' physiological states. Participants were asked to read a paragraph of text which will takes approximately 5 mins. During this task, baseline physiological measurements were recorded to monitor their responses.

Psychometric Testing (Self-report)

Participants then underwent a series of standardized self-report psychometric tests to measure various psychological constructs. The administered tests included HADS (Hospital Anxiety and Depression Scale), STAI-S (State-Trait Anxiety Inventory - State), STAI-T (State-Trait Anxiety Inventory - Trait), FQ (Fear Questionnaire), and BFI (Big Five Inventory). These tests provided subjective data on participants' anxiety, depression, personality traits, and phobic responses.

Neurophysiological Measurement

To obtain objective physiological data correlating with the psychometric test results and participants were equipped with heart rate and eye-tracking sensors. These sensors monitored heart rate variability and eye movements during the psychometric testing, providing real-time physiological data to complement the self-reported psychological data.

Synchronized Multimodal Data Collection (HuMans Software)

Using the HuMans Software which is developed by Thales, the study integrated and synchronized data from multiple sensors and psychometric tests. This software facilitated real-time collection and synchronization of data from the psychometric tests, heart rate monitors, and eye-tracking devices, ensuring accurate and cohesive data points.

Individual Longitudinal Follow-ups

Participants were subjected to follow-up assessments at one-week intervals to track changes in their psychometric and physiological data. These longitudinal follow-ups helped monitor the evolution of participants' psychological and physiological states, providing valuable data on the dynamics of their responses.

Multimodal Data Analysis

The collected data was analyzed using advanced statistical and machine learning techniques within Jupyter Notebooks. The analysis utilized Python libraries such as Pandas, NumPy, SciPy, and Scikit-learn for data manipulation and modeling. Additionally, RStudio was used for detailed statistical analysis and visualization, while tools like Matplotlib, Seaborn, and Tableau were employed to create insightful visualizations of the data. This comprehensive analysis aimed to identify patterns, correlations, and significant findings from the multimodal data.

Identification of Interindividual Differences and Styles in Psychometric Responses

The final step involved identifying individual differences in psychological responses and styles based on the analyzed multimodal data. The results from the data analysis were used to determine how different individuals responded to psychometric tests, helping to identify distinct psychological profiles and response styles. This step provided a nuanced understanding of the interindividual differences in psychometric responses.

2.1 Population

The study will employ ten participants, 18–25-year-old young adults who are proficient in both French and English, due to the fact that the student researchers for this protocol are not French speakers. Some flexibility with the language criteria will be offered: if the participants speak French and little English, they can do the tests on the computer in French and the short interview in English with supervision of an English and French speaker who can help to translate English to French and vice versa. Moreover, for the English and French speaking participants they have the option to do the short interviews in English and the tests in English or French. Exclusion criteria include physical illness, medical conditions, psychological or psychiatric conditions, and the use of any medication and psychotropic drugs.

2.2 Ethical Precautions

Before beginning the study, Participants will be presented with an information letter detailing the purpose, procedures, potential benefits, and any foreseeable risks of the study, along with an informed consent form to be carefully reviewed and signed prior to their participation. This documentation ensures that participants have a clear understanding of what is involved in the study and provides them with the opportunity to ask any questions and make an informed decision about their voluntary participation in the experiment. Participants will be provided contact numbers and emails of the researchers so that they can contact us if they have any questions or concerns at any time during the study. Participants are free to withdraw from the study at any time without justification. This research protocol is designed to be completely non-invasive, and we are committed to ensuring that each participant is treated with respect throughout their participation in the study. Possible risks may include emotional distress in answering the psychometric questions and physical discomfort from wearing the biometric sensors. First, to address any concern regarding psychological distress, researchers will offer support to encourage participants to report any emotional distress they may experience. Researchers will provide them access to mental health professionals and support services to help them cope with any emotional difficulties that may arise with the guidance of their research supervisors. If the discomfort is related to the biometric sensors, researchers will offer the participant the option to adjust the placement of the sensors or remove them temporarily. They will provide guidance on how to safely adjust or remove the sensors without compromising data collection integrity.

Psychometric and neurophysiological data will be treated and managed according to the General Data Protection Regulation (GDPR). The collected personal data is restricted to the exclusive use of the research team, for the purpose of the study. The data from the participants will be pseudonymized and will be stored in the data server of the UFR Biomedical Information Technology Service. The researchers will have access to raw data and can control the circulation of the data. With respect to the GDPR, the participants will be given access to their personal data or request that it be deleted. None of the personal data collected by the research team may be published or made public, which would be likely to allow the identification of participants. Participants also have a right of opposition, a right of rectification, and a right to limit the processing of their data. To exercise this right, the participants may reach out to the researchers on the contact information provided to them.

2.3 Data Collection

The study suggests a computer-based, iterative psychoneurometric test that modifies a "HuMans" prototype device. Motivated by the research conducted by Dimitri, Keriven Serpollet, et al. (2023) on helicopter pilots utilizing complete flight simulators, which employed neurophysiological assessments with non-invasive sensors to assess behavior and performance during simulated missions. We modify their approach to investigate if different psychological characteristics may be objectively measured in a normal functioning adult population utilizing Heart Rate Variability (HRV) and Eye-tracking sensors. Pupil dilation and fixation lengths, which are impacted by the sympathetic nervous system and may suggest increased attention associated with worry, can be observed by eye tracking. HRV measures the variation between heartbeats. During anxiety, the sympathetic nervous system increases heart rate and reduces variability. Analyzing HRV parameters provides insights into this change. HRV sensors, such as Polar H10+ and Moofit HW401, are worn by the participant to monitor heart rate variability. This data provides insights into anxiety levels and emotional state.

These sensors are easy to incorporate into psychometric tests and are comparatively non-intrusive. They provide a greater opportunity to record physiological alterations associated with the autonomic nerve system, which is central to anxiety. Researchers can create a more complete image of a test-taking participant's physiological reaction to anxiety by integrating data from multiple sensors. When utilizing multiple data sources instead of just one, the analysis is more robust. Participants will undergo a baseline reading task, followed by declarative responses to psychometric questions on the computer screen, including the Hospital Anxiety and Depression Scale (HADS), State-Trait Anxiety Inventory (STAI), 10-Item Big Five Inventory (BFI-10), and Fear Questionnaire (FQ). Following the assessment, participants will have the chance to talk about their experience and offer input, ensuring that any psychological or emotional pain is taken care of and that resources for mental health specialists are provided. It is anticipated that the entire experiment will be finished in thirty minutes.

2.4 Data Analysis Techniques

1. **Data Loading and Preprocessing**

    a. **Load Data:** Start by gathering all necessary data, including heart rate (HR), inter-beat interval (IBI), psychometric test scores, and eye-tracking data.

    b. **Clean Data:** Address any missing values in the dataset. This can be done by filling in missing values based on the last observed values or by removing records with missing data altogether. Remove noise and outliers from the dataset to ensure that the data is representative of typical conditions. Outliers can be detected using statistical methods like the Interquartile Range (IQR) and removed to prevent skewed results (Fan et al., 2021).

    c. **Preprocess Data:** Normalize or standardize the data to ensure that all variables contribute equally to the analysis. This is particularly important when combining data from different sources with varying scales. Synchronize the data from different sources by aligning the timestamps. This step ensures that all data points correspond to the same time intervals, allowing for accurate cross-comparison (Fan et al., 2021).

2. **Combine Data Sources**

    a. **Merge Datasets:** Combine datasets from different sources based on timestamps to create a unified dataset. This involves aligning data points from different sources to the same time intervals for accurate analysis. Ensure that the merged dataset maintains data integrity and consistency (Fan et al., 2021).

    b. **Feature Engineering:** Create new features, if necessary, by combining existing metrics. For example, a new feature could be the ratio of RMSSD to SDNN and calculate fixation duration which might provide additional insights (Fan et al., 2021).

3. **Calculate Metrics**

    a. **Heart Rate and HRV Metrics:** Calculate the average heart rate to get a baseline understanding of the participant's heart activity. Compute Heart Rate Variability (HRV) metrics, such as the Root Mean Square of Successive Differences (RMSSD) and the Standard Deviation of NN intervals (SDNN). These metrics provide insights into the variability in heartbeats, which is an indicator of autonomic nervous system activity (Johnson et al., 2018).

    b. **Eye-Tracking Metrics:** Determine average fixation duration, which measures how long participants focus on a particular point. Calculate average pupil size, which can be an indicator of cognitive and emotional states. Measure saccade patterns, including velocity and amplitude, to understand the rapid eye movements between fixations (Bennett et al., 2017).

c. **Psychometric Scores:** Calculate total scores for psychometric tests like the Hospital Anxiety and Depression Scale (HADS) and the State-Trait Anxiety Inventory (STAI), Big Five Inventory (BFI), Fear Questionnaire (FQ). These scores quantify the levels of anxiety and depression in participants. Categorize the anxiety levels based on predefined thresholds (e.g., normal, borderline, abnormal) to facilitate comparison across different groups.

4. **Exploratory Data Analysis (EDA) and Correlation Analysis**
   a. **Visualize Data Distributions:** Use histograms and boxplots to visualize the distribution of each metric. This helps in understanding the spread and central tendencies of the data. Plotting these distributions allows for the identification of any anomalies or patterns in the data (Fan et al., 2021).
   b. **Time Series Analysis:** Create time series plots to observe trends in heart rate, HRV, and eye-tracking metrics over the three seasons. This can reveal any temporal patterns or changes in physiological responses (Johnson et al., 2018).
   c. **Correlation Analysis:** Calculate correlation matrices to identify relationships between psychometric scores, HR, HRV, and eye-tracking metrics. This helps in understanding how different variables are interrelated. Visualize these correlations using heatmaps to easily identify strong relationships between variables.
5. **Statistical Analysis:** Calculate mean, median, standard deviation, and range for all metrics. These descriptive statistics provide a summary of the data, highlighting central tendencies and variability.

6. **Correlation and Regression Analysis:**
   a. Conduct correlation analysis to examine the relationships between different metrics, such as HRV and psychometric scores. Also, Pearson or Spearman correlation coefficients can be used depending on the data distribution.
   b. Use simple linear regression to explore the relationship between pairs of variables, such as heart rate and anxiety scores, to understand how changes in one variable predict changes in another.

7. **Hypothesis Testing:** Formulate and test hypotheses to find connection between psychometric scores such as HADS, STAI-S, STAI-T, BFI, FQ and physiological data such as HRV and Fixation Duration. Use p-values from statistical tests to determine the significance correlation. A p-value less than 0.05 typically indicates statistical significance (Fan et al., 2021).

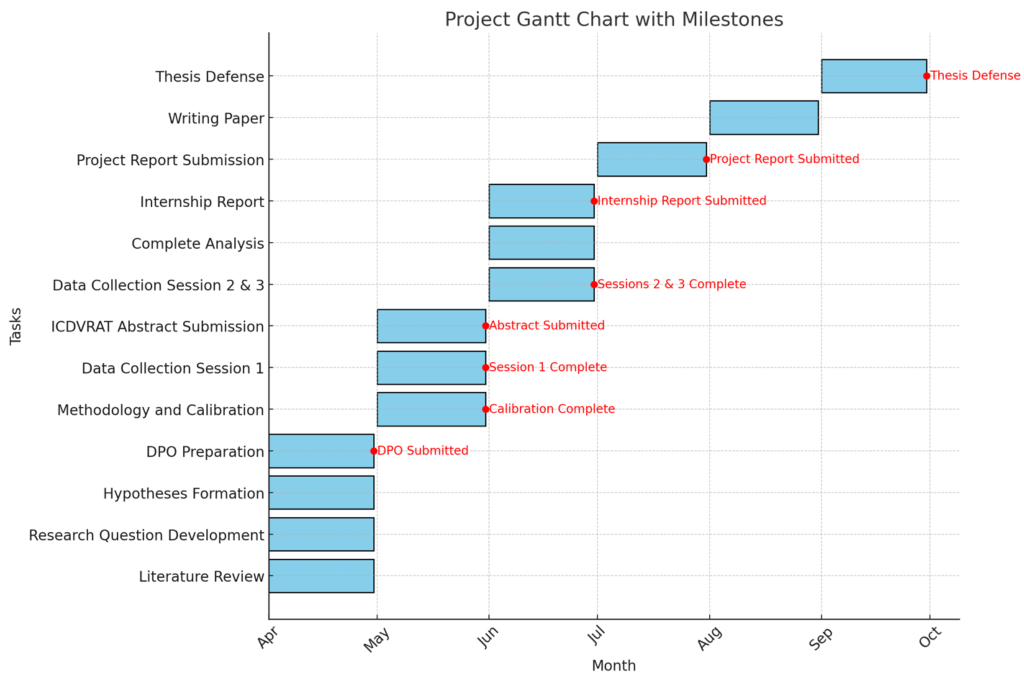
8. **Validation and Testing:** Split the data into training and testing sets to validate the findings. This ensures that the results are not due to overfitting and are generalizable to new data. Perform statistical tests on both the training and testing sets to confirm the robustness of the results (Fan et al., 2021).

9. **Compare Diagnostic Performance:** Compare the performance of combined data sources against individual data sources to assess the added value of integrating multiple types of data. This comparison can highlight the effectiveness of using combined metrics for better diagnostics.

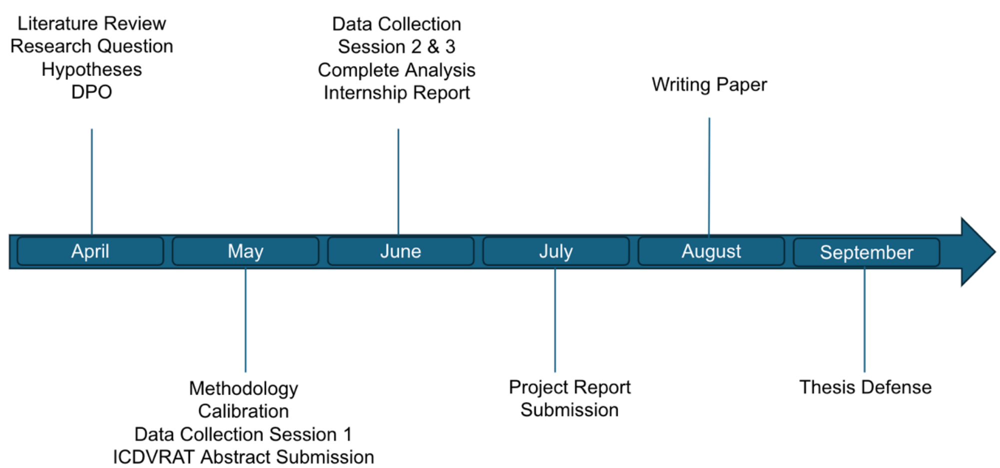
10. **Interpretation and Reporting:** Interpret the results of the statistical tests to understand whether combining psychometric tests with heart rate and eye-tracking data improves anxiety diagnostics. Analyze the significance levels and effect sizes to determine the strength and importance of the findings.

2.2. Implementation Process

2.2.1. GANTT Chart



2.2.2 Milestone Calendars



3.1 Hardware

3.1.1 Sensor Technology

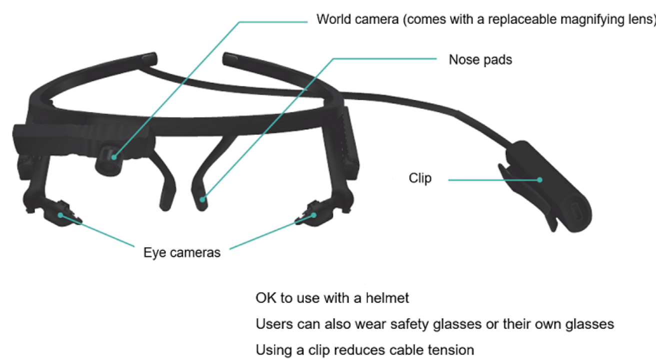
Sensor technology encompasses various devices that detect and measure physical properties, providing critical data for a wide range of applications. These technologies are essential in fields such as medicine, engineering, and research, enabling precise monitoring and analysis.

Eye-Tracking

Eye-tracking technology measures where and how long a person looks at various stimuli, providing insights into visual attention and cognitive processes. It is used in diverse areas such as psychology, neuroscience, marketing, and human-computer interaction.

Pupil Labs Core

The Pupil Labs Core is an advanced eye-tracking system known for its high precision and versatility. It has high sampling rate for extensive data recording, 3D gaze estimation for thorough real-world tracking, and open-source software for customization.



- **Open-Source Software:** Pupil Labs offers open-source software (Pupil Capture) which allows for greater customization and integration for specific research needs.

- **Higher Sampling Rate:** Pupil Labs Core boasts a 200 Hz sampling rate, higher rate captures more detailed eye movement data, potentially leading to more precise analysis, especially for fast eye movements during the experiments.

- **3D Gaze Estimation:** A 3D gaze estimate function is available in Pupil Labs Core, which can be useful if your research involves tracking gaze in real-world settings in addition to 2D screens.

Face Movement

AXIS P1245 and P1275 offer high definition (HD) 1080p resolution, which captures more facial details compared to lower resolution cameras (Axis Communications, n.d.).

- **Lighting**: Many indoor AXIS cameras have good low-light performance. OpenFace often works best with well-lit faces.

- **Frame Rate:** AXIS cameras typically offer high frame rates (e.g., 30 frames per second). This captures subtle and rapid change in facial expressions that OpenFace can analyze.

Difference between OpenFace and Noldus:

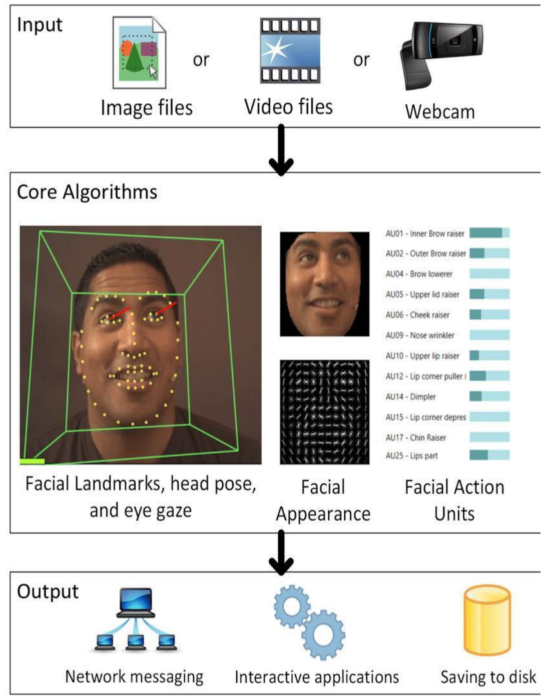
OpenFace is open-source, freely accessible, and customizable, while Noldus FaceReader is a commercial software requiring a license.

Features	OpenFace	Noldus
Description	Open-source, facial behavior analysis toolkit	Commercial software for facial expression analysis
Pros	- Open-source, freely available	- Sophisticated algorithms for facial expression analysis
	- Extensible and customizable	- Widely used in psychology, neuroscience, and market research
	- Supports various facial analysis tasks: 1. facial landmark detection 2. head pose estimation. 3. facial action unit recognition 4. eye-gaze estimation.	- Accurate detection of a wide range of facial expressions
Cons	- May lack some advanced features	- Costly for individual researchers or small organizations
		- Limited flexibility for customization compared to open-source alternatives.

OpenFace

Input

OpenFace can accept images, videos, or live webcam feed as input.



Core Algorithms

- Facial Landmark Detection and Tracking (FLDT) uses computer vision to identify key points on a face to track movements.
- Head Pose Tracking (HPT) estimates head rotation and position using these landmarks.
- Eye Gaze Estimation (EGE) determines gaze direction by analyzing eye landmarks.
- Facial Action Unit Recognition (FAUR) estimates expressions by analyzing facial landmarks and Action Units (AUs).

Output

The results (facial landmarks, head pose, eye gaze and facial expressions) can be saved to disk for later study, utilized in interactive programs, or transmitted to other apps via network messaging.

Skin Conductance

The electrical conductivity of the skin, which fluctuates with its moisture content, is measured by skin conductance, sometimes referred to as galvanic skin response (GSR). Sweat gland activity, which is governed by the sympathetic nervous system, affects this physiological reaction. Consequently, skin conductance is frequently employed as a marker of physiological or psychological arousal, including tension, excitement, or worry.

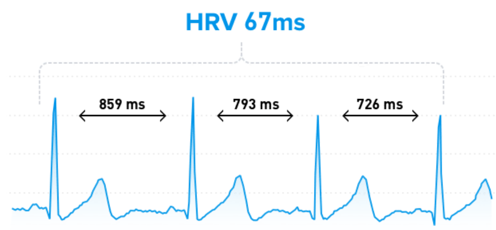
TEA CAPTIV T-SENS GSR

The TEA CAPTIV T-SENS GSR is a device designed to measure skin conductance. The T-SENS GSR sensor captures real-time data on skin conductance, providing valuable insights into a person's emotional and physiological state.

- **High Sensitivity and Accuracy:** The TEA CAPTIV T-SENS GSR provides precise and reliable measurements of skin conductance, ensuring high-quality data for research and analysis.
- **Real-time Monitoring:** The device allows for continuous real-time monitoring of skin conductance, which is crucial for studying dynamic physiological responses to different stimuli or conditions.
- **User-friendly Integration:** It easily integrates with other TEA CAPTIV sensors and software, offering a comprehensive solution for multi-dimensional physiological and behavioral research.

Heart Rate Variability

Heart Rate Variability (HRV) measures the variation in time intervals between consecutive heartbeats. It is an important indicator of the autonomic nervous system's function which is related with anxiety. Higher HRV generally indicates better cardiovascular fitness and resilience to stress, while lower HRV can be a sign of stress, fatigue, or health issues.



Polar H10+

The Polar H10+ is a high-precision heart rate sensor widely used in fitness and health monitoring. It provides accurate HRV data and is compatible with various fitness apps and devices. Its reliable chest strap ensures a secure fit and higher accuracy of HR data.

Moofit HW401

Moofit is a cost-effective heart rate monitor that offers HRV tracking, it provides accurate real-time data on heart rate.

3.1.2 Multimodal and Multi-sensor Approaches

Sensors	Software	Specifications	Parameters
Eye Tracking (Pupil Labs Core) (Meo et al., 2024).	Pupil Capture Software	- Technology: Dark pupil + 3D model - Calibration: 5 points - Resolutions: 1080p @30 Hz, 720p @60 Hz, 480p @120 Hz	- Fixation Duration - Gaze Point - Saccades - Blinks - Pupil Size - Eye Movements
Face Movements (Camera AXIS P1275, P1245) (Khan et al., 2024)	OpenFace Software	- Resolution: HDTV 1080p - Capture: WDR – Forensic - Field of view: 53°-99° horizontal & 111° horizontal	- Facial Landmarks - Facial Expressions - Facial Action Units - Head Pose - Gaze Direction
Skin Conductance (TEA GSR) (Dean et al., 2013)	CAPTIV Software	- Sampling rate: 32 hz - Compact and Lightweight: 20g - Long Battery Life: 8 hrs.	- Sample Rate - Filtering - Skin Conductance Level (SCL) - Skin Conductance Response (SCR)
HRV (Polar H10+, Moofit HW401) (Burma et al., 2024)	Polar Flow Software	- Microprocessor speed: 64 MHz - Sensors: ECG	Time-Domain Parameters • Standard Deviation of Normal RR Intervals (SDNN) • Root Mean Square of Successive Differences (RMSSD) Frequency-Domain Parameters • Low-Frequency (LF) • High-Frequency (HF) • LF/HF ratio

4.1 Software

4.1.1 HuMans Software

HuMans Software, originally developed by Thales for helicopter pilot assessments, plays an important role in our research by facilitating the integration of multi-sensor data to assess the neurophysiological responses during psychometric testing. The software's advanced capabilities enable comprehensive monitoring and evaluation of participants' physiological states in real-time.

1. **Integration of Multi-Sensor Data**
    - **Sensor Setup and Configuration:** HuMans Software integrates various sensors, including eye-tracking devices (Pupil Labs Core) and heart rate variability sensors (Polar H10+ and Moofit HW401). These sensors are configured within the software to ensure synchronized data collection.

2. **Real-Time Monitoring and Visualization**
    - **Dashboard Interface:** The software provides a user-friendly dashboard that displays real-time data streams from the sensors. This interface allows researchers to monitor participants' physiological responses during the psychometric tests.
    - **Data Visualization:** As shown in the provided image, the dashboard visualizes various parameters such as heart rate, inter-beat interval (IBI), and confidence levels. These visualizations help in identifying immediate physiological changes in response to the tests.

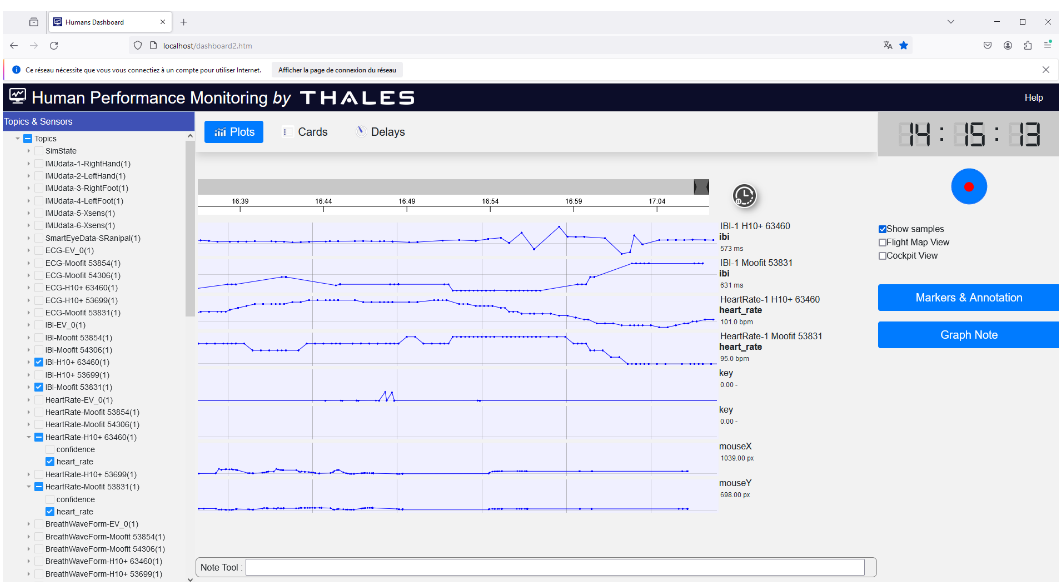


Fig: Thales Human Performance Monitoring for Data Collection

3. **Data Synchronization and Management**
   - **Data Synchronization:** HuMans Software synchronizes data from multiple sensors, which ensuring that all collected data points are accurately time-stamped. This synchronization is critical for correlating physiological responses with specific moments during the psychometric tests.
   - **Automated Data Collection:** HuMans Software automatically collects and logs physiological data, reducing the need for manual data entry and minimizing potential errors.

4.1.2 Psychometric Test Software

The Psychometric Test Software developed for this project is a comprehensive web-based application designed to administer various psychometric tests (HADS, STAI-S, STAI-T, BFI, FQ), record user responses, and generate summarized and detailed results. The software is implemented using modern web technologies, providing a user-friendly interface and robust data management capabilities. Psychometric Test is developed in English and French, making it versatile for diverse user groups.

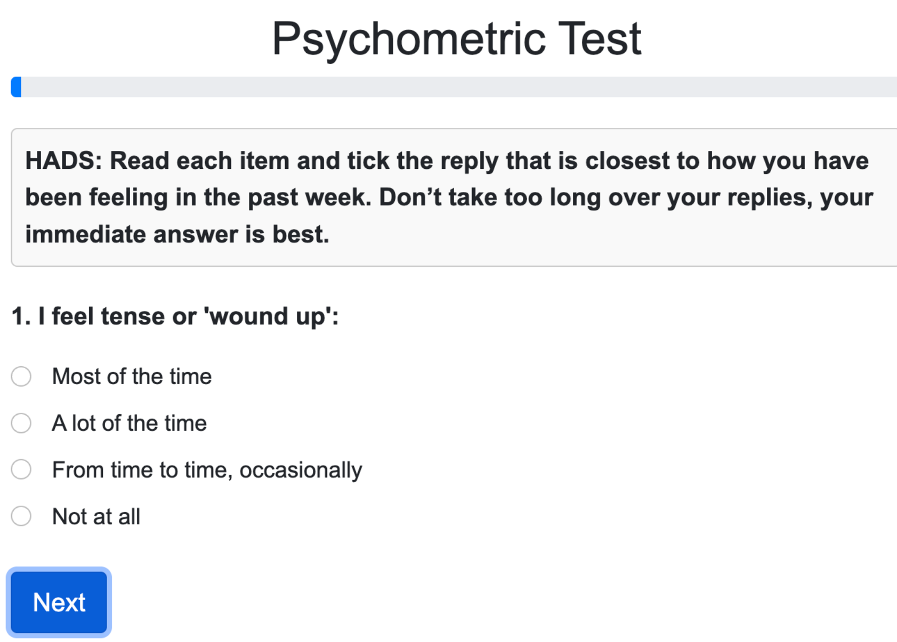


Fig: Psychometric Test Software

Technologies Used

1. **HTML:** Defines the structure of the web interface.
2. **CSS:** Styles the web interface to ensure a clean and user-friendly design.
3. **JavaScript:** Manages dynamic functionalities, including test navigation, answer recording, and result generation.
4. **Bootstrap:** Provides responsive design and styling components.
5. **jQuery:** Simplifies DOM manipulation and event handling.
6. **jsPDF:** Facilitates the generation of PDF files for the test results.

Psychometric Tests Included

The software incorporates several standardized psychometric tests, each with a specific scoring system:

1. **HADS (Hospital Anxiety and Depression Scale)**

   - Measures levels of anxiety and depression.

   - Scores are categorized into Anxiety and Depression subscales.

2. **STAI-S (State-Trait Anxiety Inventory - State)**

   - Evaluates current state anxiety.

   - Each question is scored on a scale from 1 to 4.

3. **STAI-T (State-Trait Anxiety Inventory - Trait)**

   - Assesses general anxiety traits over time.

   - Similar scoring system to STAI-S.

4. **BFI (Big Five Inventory)**

   - Assesses personality traits across five dimensions: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

   - Scores range from 1 to 5 for each trait-related question.

5. **FQ (Fear Questionnaire)**

   - Measures specific phobias and overall anxiety.

   - Scores range from 0 to 8, indicating the severity of avoidance or fear.

Interface and Functionality

The software is structured into several key components to ensure efficient administration, data recording, and result generation.

1. **User Interface**
   - **HTML Structure:** Provides the framework for displaying test instructions, questions, and navigation buttons.
   - **CSS Styling:** Ensures a visually appealing and consistent design, enhancing the user experience.
   - **Bootstrap Integration:** Adds responsive design elements and styled components, such as buttons and progress bars.

2. **Dynamic Functionality with JavaScript**
   - **Initialization:** Sets up variables to track the current test, question index, total questions, and user responses.
   - **Event Handling:** Manages user interactions, such as starting the test, navigating questions, and downloading results.

3. **Test and Question Management**
   - **loadTest(test):** Loads the instructions and questions for the selected test.
   - **loadQuestion(question):** Dynamically displays each question and its answer options and updates the progress bar.

4. **Progress Bar**
   - **updateProgressBar():** Displays the user's progress through the test, updating dynamically as each question is answered.

5. **Answer Recording**
   - **recordAnswer():** Captures the user's selected answer, calculates the time taken to respond, and logs this data with timestamps.
   - **Data Storage:** Responses are stored in an array for further analysis and reporting.

6. **Result Generation**
   - **generateCSV()**: Constructs a CSV file with the recorded answers and their metadata.
   - **generatePDF()**: Creates a PDF report summarizing the scores and detailed responses using jsPDF.

Psychometric_Test_Results

Delimiter: ,

	Psychometric Tests	Question	Answer	Score	Time(s)	Question Start Time	Question Answer Time	Anxiety Question
1	HADS	1. I feel tense or 'wound up':	From time to time; occasionally	1	9.551	2024-06-06T13:41:54.041Z	2024-06-06T13:42:03.593Z	Anxiety
2	HADS	2. I still enjoy the things I used to enjoy:	Definitely as much	0	7.984	2024-06-06T13:42:03.593Z	2024-06-06T13:42:11.577Z	
3	HADS	g as if something awful is about to happen:	Not at all	0	7.599	2024-06-06T13:42:11.577Z	2024-06-06T13:42:19.176Z	Anxiety
4	HADS	can laugh and see the funny side of things:	As much as I always could	0	8.136	2024-06-06T13:42:19.176Z	2024-06-06T13:42:27.312Z	
5	HADS	5. Worrying thoughts go through my mind:	From time to time; but not too often	1	6.024	2024-06-06T13:42:27.312Z	2024-06-06T13:42:33.336Z	Anxiety
6	HADS	6. I feel cheerful:	Sometimes	1	5.512	2024-06-06T13:42:33.336Z	2024-06-06T13:42:38.848Z	
7	HADS	7. I can sit at ease and feel relaxed:	Usually	1	10.889	2024-06-06T13:42:38.848Z	2024-06-06T13:42:49.737Z	Anxiety
8	HADS	8. I feel as if I am slowed down:	Sometimes	1	16.583	2024-06-06T13:42:49.737Z	2024-06-06T13:43:06.320Z	
9	HADS	ened feeling like 'butterflies' in the stomach:	Not at all	0	16.952	2024-06-06T13:43:06.320Z	2024-06-06T13:43:23.272Z	Anxiety
10	HADS	10. I have lost interest in my appearance:	I take just as much care as ever	0	9.096	2024-06-06T13:43:23.272Z	2024-06-06T13:43:32.368Z	
11	HADS	I feel restless as I have to be on the move:	Not very much	1	17.384	2024-06-06T13:43:32.368Z	2024-06-06T13:43:49.752Z	Anxiety
12	HADS	12. I look forward with enjoyment to things:	Rather less than I used to	1	15.432	2024-06-06T13:43:49.752Z	2024-06-06T13:44:05.184Z	
13	HADS	13. I get sudden feelings of panic:	Not very often	1	4.688	2024-06-06T13:44:05.184Z	2024-06-06T13:44:09.872Z	Anxiety
14	HADS	enjoy a good book or radio or TV program:	Sometimes	1	10.777	2024-06-06T13:44:09.872Z	2024-06-06T13:44:20.649Z	
15	STAI-S	1. I feel calm.	Very much	1	12.424	2024-06-06T13:44:20.649Z	2024-06-06T13:44:33.073Z	Anxiety
16	STAI-S	2. I feel secure.	Somewhat	3	5	2024-06-06T13:44:33.073Z	2024-06-06T13:44:38.073Z	Anxiety
17	STAI-S	3. I am tense.	Somewhat	2	11.111	2024-06-06T13:44:38.073Z	2024-06-06T13:44:49.184Z	Anxiety
18	STAI-S	4. I feel regretful.	Not at all	1	3.112	2024-06-06T13:44:49.184Z	2024-06-06T13:44:52.296Z	Anxiety
19	STAI-S	5. I feel at ease.	Somewhat	3	12.128	2024-06-06T13:44:52.296Z	2024-06-06T13:45:04.424Z	Anxiety
20	STAI-S	6. I feel upset.	Not at all	1	3.008	2024-06-06T13:45:04.424Z	2024-06-06T13:45:07.432Z	Anxiety
21	STAI-S	rrently worried about possible misfortunes.	Not at all	1	4	2024-06-06T13:45:07.432Z	2024-06-06T13:45:11.432Z	Anxiety
22	STAI-S	8. I feel rested.	Somewhat	3	6.408	2024-06-06T13:45:11.432Z	2024-06-06T13:45:17.840Z	Anxiety
23	STAI-S	9. I feel anxious.	Not at all	1	7.824	2024-06-06T13:45:17.840Z	2024-06-06T13:45:25.664Z	Anxiety

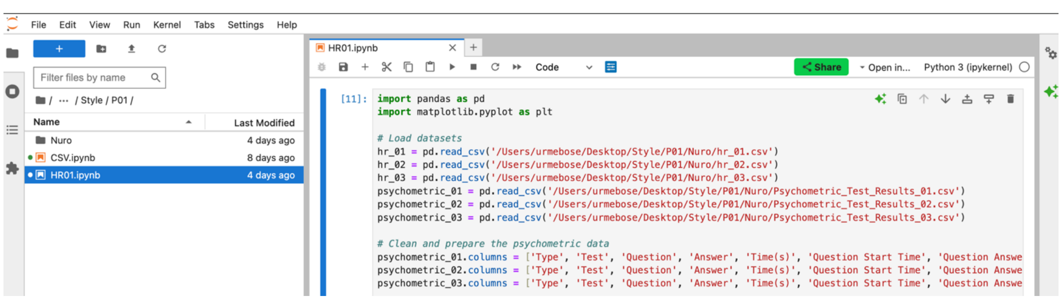
Fig: CSV file of Psychometric Tests

4.1.3 Data Analysis Tools

In this project, various data analysis tools were employed to ensure comprehensive data processing, statistical analysis, and insightful visualization. These tools were essential for interpreting the results of the psychometric tests and integrating them with the neurophysiological data collected.

1. **Jupyter Notebook:** Integrated Development Environment (IED) for coding, analysis, and visualization.

The data collected from the psychometric tests and sensors were loaded into Jupyter Notebooks for initial cleaning and exploration. For instance, Python code to load and display the data might look like this:



2. **Python Libraries:** Pandas, NumPy, SciPy, Scikit-learn for data manipulation and modeling

Pandas: Used for data manipulation and analysis. It provided data structures like DataFrame to efficiently handle large datasets.

Example: Filtering the data to focus on responses from a specific psychometric test.

```
import pandas as pd

# Load the txt file using ';' as delimiter
file_path = '/Users/urmebose/Desktop/Style/P01/Nuro/hr.txt'
df = pd.read_csv(file_path, delimiter=';')

# Save the dataframe to a CSV file
csv_file_path = '/Users/urmebose/Desktop/Style/P01/Nuro/hr.csv'
df.to_csv(csv_file_path, index=False)

csv_file_path
```

```
'/Users/urmebose/Desktop/Style/P01/Nuro/hr.csv'
```

NumPy: Utilized for numerical operations and handling arrays.

Example: Calculating mean scores for HADS Anxiety and Depression subscales.

```
import numpy as np

hads_anxiety_scores = hads_data[hads_data['Category'] == 'Anxiety']['Score']
hads_depression_scores = hads_data[hads_data['Category'] == 'Depression']['Score']

mean_anxiety = np.mean(hads_anxiety_scores)
mean_depression = np.mean(hads_depression_scores)

print(f"Mean Anxiety Score: {mean_anxiety}")
print(f"Mean Depression Score: {mean_depression}")
```

SciPy: Used for statistical analysis and scientific computations.

Example: Performing a t-test to compare the mean scores of two different tests.

```
from scipy.stats import ttest_ind

stai_s_scores = data[data['Test'] == 'STAI-S']['Score']
stai_t_scores = data[data['Test'] == 'STAI-T']['Score']

t_stat, p_val = ttest_ind(stai_s_scores, stai_t_scores)
print(f"T-statistic: {t_stat}, P-value: {p_val}")
```

Scikit-learn: Employed for machine learning and predictive modeling.

Example: Building a predictive model to classify levels of anxiety based on test scores.

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

# Preparing the data
X = data[['HADS_Anxiety', 'HADS_Depression', 'STAI-S', 'STAI-T', 'BFI', 'FQ']]
y = data['Anxiety_Level']

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Training the model
model = RandomForestClassifier()
model.fit(X_train, y_train)

# Predicting
predictions = model.predict(X_test)
```

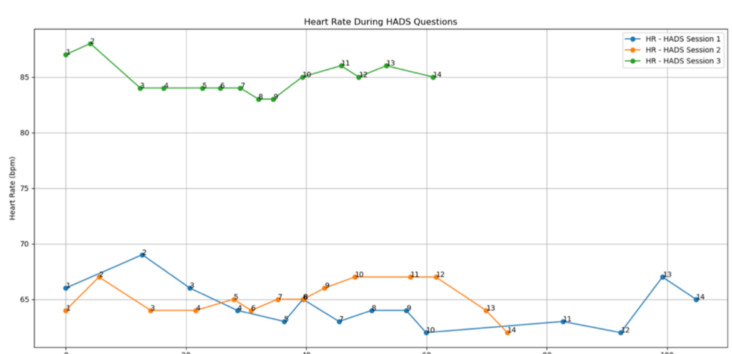
3. **Data Visualization Tools:** Matplotlib, Seaborn, and Tableau for creating insightful visualizations.

Matplotlib: A versatile library for creating static, animated, and interactive visualizations in Python.

Example: Plotting a histogram of the heart rate.

```
import matplotlib.pyplot as plt

    plt.hist(hads_anxiety_scores, bins=10, alpha=0.7, color='blue')
    plt.xlabel('Time Difference (seconds)')
    plt.ylabel('Heart Rate (bpm)')
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()

for q_type in question_types:
    process_and_plot(q_type)
```

Results



Seaborn: Built on top of Matplotlib, it provides a high-level interface for drawing attractive and informative statistical graphics.

Example: Creating a boxplot to visualize the distribution of scores across different tests.

```
import seaborn as sns

# Display the results
print("Total Timing During 3 Sessions")
print(session_stats)

# Plot the answer duration for each session
plt.figure(figsize=(12, 6))
sns.boxplot(data=all_sessions, x='Session', y='answer_duration')
plt.title('Comparison of Answer Duration Across Sessions')
plt.ylabel('Answer Duration (minutes)')
plt.xlabel('Session')
plt.show()
```

Result

```
Total Timing During 3 Sessions
      Session  Count  Total Timing (minutes)  Standard Deviation (minutes)
0  Session 01     88                8.476250                      0.051756
1  Session 02     88                6.496800                      0.026749
2  Session 03     88                5.013317                      0.022352
```

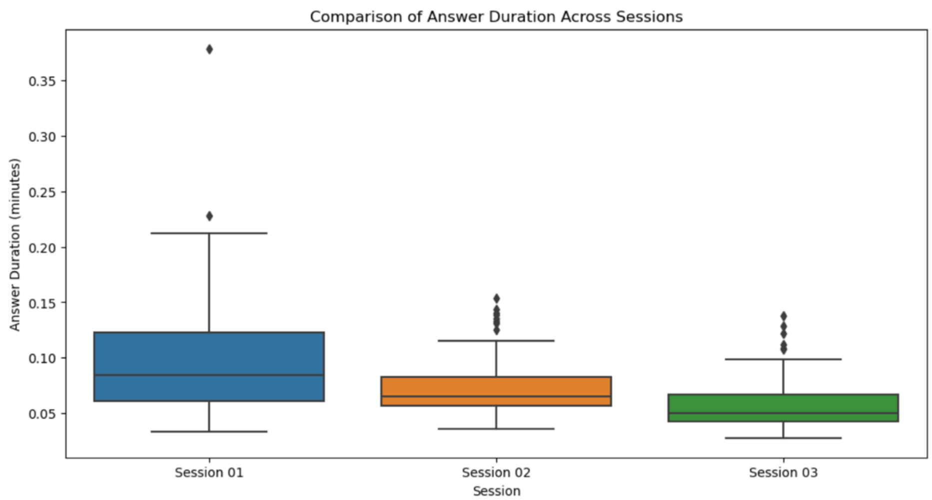


Tableau: Used for creating interactive and shareable dashboards.

Example: Visualizing the summary scores and detailed responses in an interactive dashboard that allows for dynamic filtering and drill-down into specific data points.

```
from tabulate import tabulate

# Plot each participant's 3 sessions time separately
plt.figure(figsize=(15, 8))
sns.catplot(x='Session', y='Total Timing (minutes)', col='Participant', data=session_stats, kind='bar'
plt.subplots_adjust(top=0.9)
plt.suptitle('Total Timing for Each Session by Participant')
plt.show()
```

Result

Total Timing During 3 Sessions for Each Participant

	Participant	Session	Count	Total Timing (minutes)	Standard Deviation (minutes)
0	P01	Session 01	88	10.34	0.06
1	P01	Session 02	88	10.8	0.09
2	P01	Session 03	88	11.4	0.12
3	P02	Session 01	88	5.98	0.05
4	P02	Session 02	88	4.49	0.04
5	P02	Session 03	88	4.44	0.04
6	P03	Session 01	88	8.48	0.05
7	P03	Session 02	88	6.5	0.03
8	P03	Session 03	88	5.01	0.02
9	P04	Session 01	88	13.41	0.1
10	P04	Session 02	88	11.07	0.11
11	P04	Session 03	88	10.03	0.08
12	P05	Session 01	88	11.99	0.08
13	P05	Session 02	88	8.63	0.06
14	P05	Session 03	88	7.69	0.05

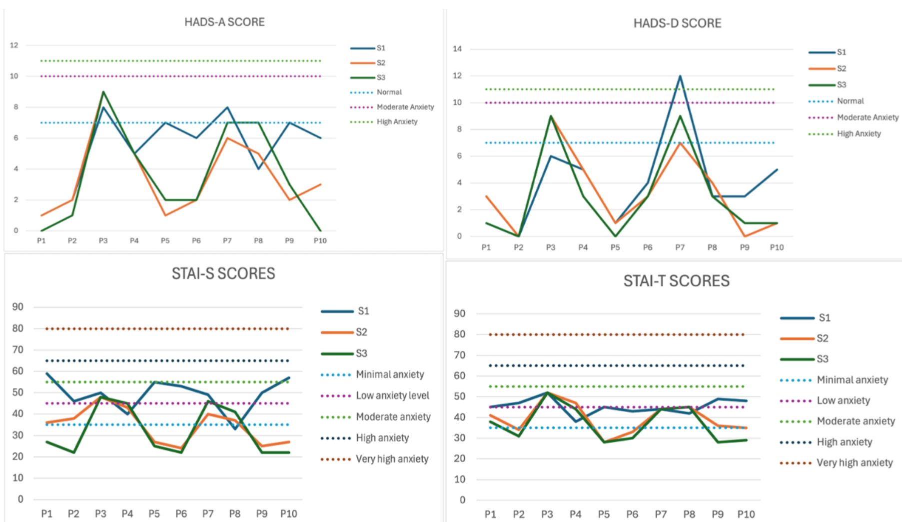
Chapter 3: Conclusion

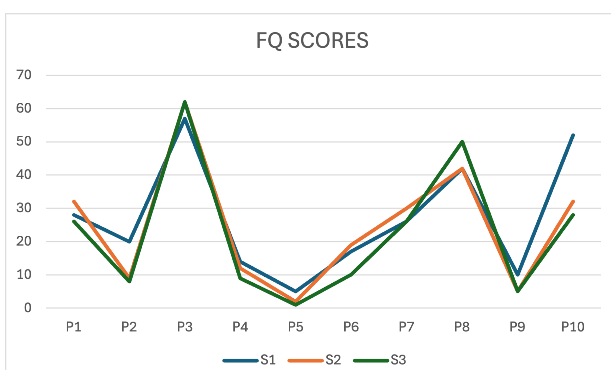
3.1 Results

Data collected from 10 participants across three sessions revealed significant findings, particularly for Participants 3 and 7, who exhibited the highest levels of anxiety. A variety of parameters are considered, such as Psychometric Score, duration of answer time on Psychometric test, heart rate variability, pupil dilation and left and right eye blink rates.

3.1.1 Psychometric Score Analysis

Participants 3 and 7 exhibit the highest levels of anxiety (HADS-A), depression (HADS-D), introversion, conscientiousness (BFI-10), and phobia (FQ) across three sessions. Descriptive statistics and ANOVA analyses reveal consistently high scores for these traits, indicating significant psychological distress and stable personality characteristics. These findings make Participants 3 and 7 critical case studies, demonstrating the project's hypothesis that individual differences significantly impact psychometric scores.





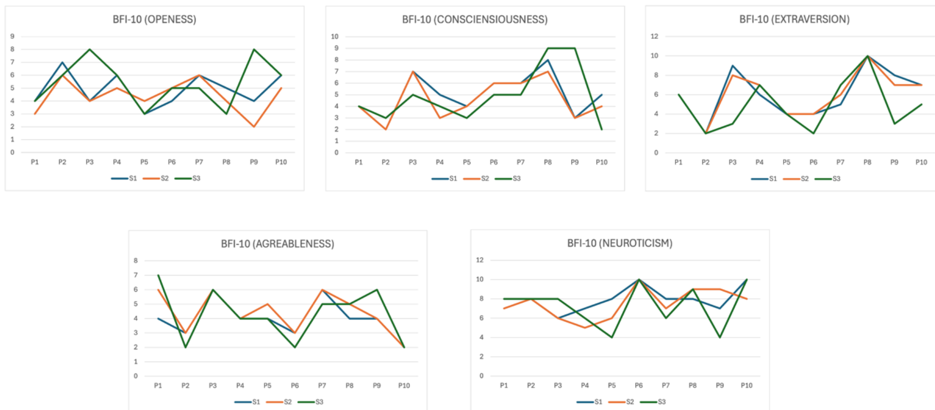


Fig: Psychometric Score Analysis for 10 Participants (HADS, STAI-S, STAI-T, BFI, FQ)

To understand whether there is a significant difference between the mean scores of the psychometric test scores among participants and across the three sessions, a repeated measures analysis was done through ANOVA Two-Factor Without Replication for each tests.

ANOVA

Psych Test	*Source of Variation*	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
HADS-A	Participants	146.17	9	16.24	6.48	0.00	2.46
	Sessions	26.87	2	13.43	5.36	0.01	3.55
HADS-D	Participants	239.47	9	26.61	20.01	1.26	2.46
	Sessions	16.07	2	8.03	6.04	0.01	3.55
STAI-S	Participants	668.3	9	74.26	0.69	0.71	2.46
	Sessions	1484.6	2	742.3	6.89	0.01	3.55
STAI-T	Participants	683.63	9	75.96	2.10	0.09	2.46
	Sessions	362.6	2	181.3	5.00	0.02	3.55
FQ	Participants	8798.83	9	977.65	35.94	1.08	2.46
	Sessions	105	2	52.5	1.93	0.17	3.55
FQ subscale	Participants	956.53	9	106.28	25.69	1.71	2.46
	Sessions	4.87	2	2.43	0.59	0.57	3.55
BFI-10 (O)	Participants	33.63	9	3.74	7.59	0.00	2.46
	Sessions	0.47	2	0.23	0.47	0.63	3.55
BFI-10 (C)	Participants	97.87	9	10.87	24.67	2.37	2.46
	Sessions	1.4	2	0.7	1.59	0.23	3.55
BFI-10 (E)	Participants	164.03	9	18.23	30.76	3.92	2.46
	Sessions	2.84	2	1.42	2.39	1	3.55
BFI-10 (A)	Participants	48.53	9	5.39	8.93	0.00	2.46
	Sessions	0.47	2	0.23	0.39	0.68	3.55
BFI-10 (N)	Participants	52	9	5.78	7.12	0.00	2.46
	Sessions	0.07	2	0.03	0.04	0.96	3.55

Fig: ANOVA results of all participants' psychometric test results across three sessions.

Psychometric Test Anxiety Thresholds

Psychometric test anxiety thresholds refer to the specific levels on standardized tests, such as the Hospital Anxiety and Depression Scale (HADS) and State-Trait Anxiety Inventory (STAI), that indicate varying degrees of anxiety.

Test	Score Range	Anxiety Level
HADS	0-7	Normal
	8-10	Moderate Anxiety
	11-14	High Anxiety
STAI-S	20-35	Minimal Anxiety
	36-45	Low Anxiety
	46-55	Moderate Anxiety
	56-65	High Anxiety
	66-80	Very High Anxiety
FQ- A	0-40	Anxiety and Depression

3.1.2 Duration Analysis

The analysis of psychometric test results over three sessions shows a clear trend of decreasing answer duration, with total times reducing from 8.48 minutes in Session 01 (SD: 0.052 minutes) to 6.50 minutes in Session 02 (SD: 0.027 minutes) and further to 5.01 minutes in Session 03 (SD: 0.022 minutes). This reduction in time can be attributed to the habituation effect, where participants become more accustomed to the testing environment and procedures over repeated sessions.

Total Timing During 3 Sessions

	Session	Count	Total Timing (minutes)	Standard Deviation (minutes)
0	Session 01	88	8.476250	0.051756
1	Session 02	88	6.496800	0.026749
2	Session 03	88	5.013317	0.022352

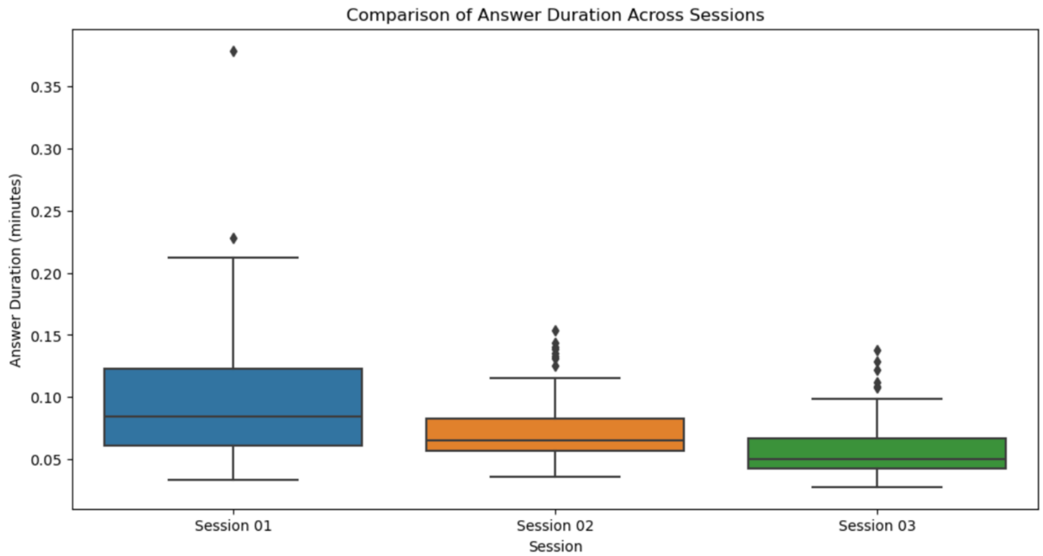
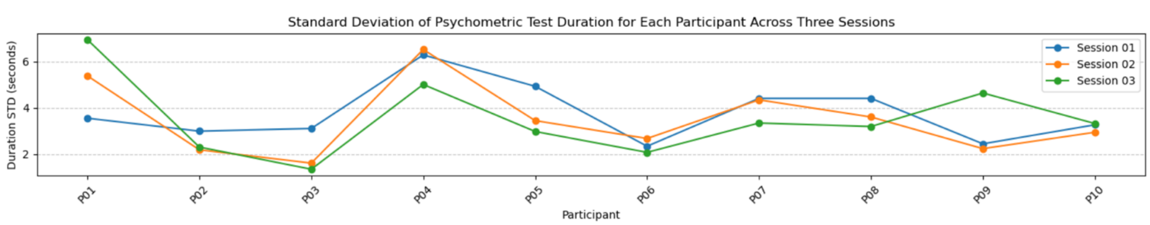


Fig: Answer Duration of P3

The total timing for each of the 10 participants across three sessions shows a general trend of decreasing duration over successive sessions, indicating a potential habituation or learning effect. Notably, participants P01, P05, and P08 exhibit a marked reduction in total timing from Session 01 to Session 03, suggesting increased efficiency or familiarity with the tasks over time.



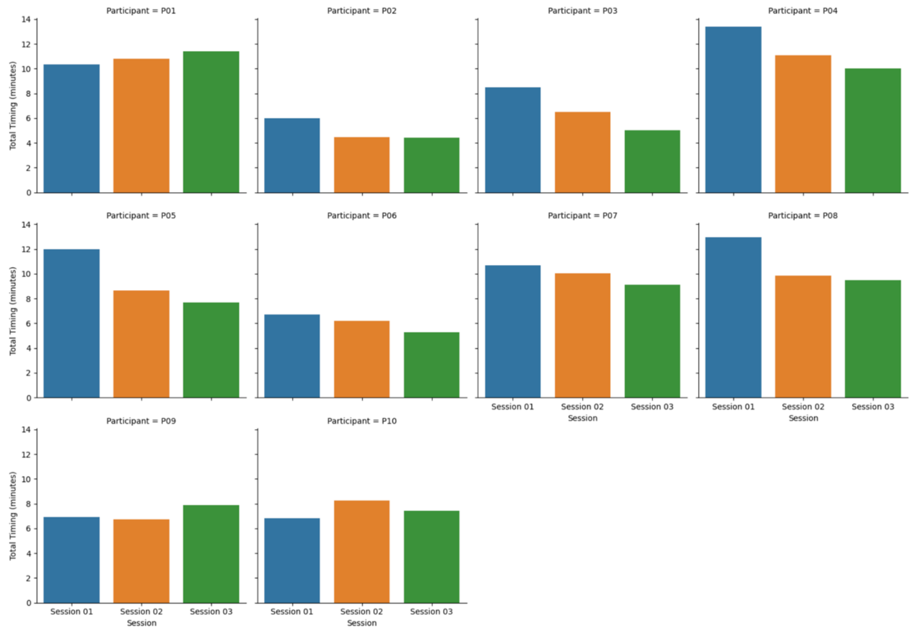


Fig: Duration Analysis of 10 participants over three sessions

The standard deviation of psychometric test duration shows varying trends across participants. Participants such as P01 and P04 exhibit a clear decrease in variability over the three sessions, indicating that they became more consistent in their response times, likely due to habituation or learning effects. In contrast, participants like P02 and P03 maintained relatively low variability, with P03 showing a slight decrease over time. Participants P05, P07, and P08 displayed fluctuating patterns, reflecting more variable changes in test durations. Lastly, participants like P06 and P10 demonstrated stable standard deviations across sessions, indicating consistent timing in their responses. These trends suggest that while some participants improved their consistency, others experienced more variability, highlighting individual differences in adaptation and response patterns.

3.1.3 Eye-Tracking Metrics Analysis

Eye tracking metrics were higher across all psychometric tests (HADS, STAI-S, STAI-T, BFI, FQ) than the baseline. During Test 01, average pupil dilation increased across all the questionnaires, indicating heightened cognitive load or anxiety, while blink rates remained close to baseline levels, suggesting initial adjustment. In Test 02, there was a notable decrease in pupil dilation, indicating reduced engagement or adaptation, but a significant spike in blink rates, especially in the STAI-S (left: 65.57 blinks/min, right: 85.56 blinks/min) and FQ (left: 77.16 blinks/min, right: 146.31 blinks/min), reflecting heightened cognitive load or stress. By Test 03, both metrics showed partial recovery, with increased pupil dilation and decreased, yet elevated, blink rates compared to the baseline, indicating a combination of habituation and sustained cognitive engagement.

```
Eye-Tracking Metrics:
Baseline Metrics:
  Start Time: 2024-06-05 10:44:55.920900
  End Time: 2024-06-05 10:46:42.806900
  Total Duration: 1.78 minutes
  Average Pupil Dilation: 2.51
  Left Blink Rate: 15.72 blinks/min
  Right Blink Rate: 16.84 blinks/min

Test 01 Metrics:
  Start Time: 2024-06-13 11:30:10.520900
  End Time: 2024-06-13 11:39:05.498900
  Total Duration: 8.92 minutes
  Average Pupil Dilation: 2.82
  Left Blink Rate: 17.05 blinks/min
  Right Blink Rate: 21.08 blinks/min

Test 02 Metrics:
  Start Time: 2024-06-20 09:41:01.850900
  End Time: 2024-06-20 09:47:57.391900
  Total Duration: 6.93 minutes
  Average Pupil Dilation: 1.94
  Left Blink Rate: 61.51 blinks/min
  Right Blink Rate: 90.68 blinks/min

Test 03 Metrics:
  Start Time: 2024-06-24 12:48:29.702900
  End Time: 2024-06-24 12:53:52.131900
  Total Duration: 5.37 minutes
  Average Pupil Dilation: 2.26
  Left Blink Rate: 43.92 blinks/min
  Right Blink Rate: 46.71 blinks/min
```

The findings demonstrate that neurophysiological responses, such as pupil dilation and left blink rates and right blink rates, correlate with psychological states as measured by psychometric tests. The significant increase in blink rates during Test 02 across various questionnaires highlights periods of high anxiety or cognitive load, while the recovery in Test 03 suggests adaptation over time. Additionally, the consistent patterns observed most of the participants.

Test	Type	Start Time	End Time	Average Pupil Dilation	Left Blink Rate	Right Blink Rate
Test 01	HADS	11:30:18	11:32:10	2.841711	13.913168	13.378046
Test 02	HADS	09:41:08	09:42:25	1.949553	9.399478	14.099217
Test 03	HADS	12:48:35	12:49:38	2.357059	16.096452	17.043303
Test 01	STAI-S	11:32:10	11:34:04	2.751345	25.183410	35.151844
Test 02	STAI-S	09:42:25	09:43:40	1.593644	65.565906	85.555511
Test 03	STAI-S	12:49:38	12:50:32	2.255183	28.851489	34.399852
Test 01	STAI-T	11:34:04	11:35:30	2.854124	11.928708	14.735463
Test 02	STAI-T	09:43:40	09:45:00	1.712913	69.996739	90.318372
Test 03	STAI-T	12:50:32	12:51:30	2.161578	45.875545	47.960797
Test 01	BFI	11:35:30	11:36:06	2.865006	9.778888	14.668333
Test 02	BFI	09:45:00	09:45:39	2.282301	45.061377	59.045942
Test 03	BFI	12:51:30	12:52:06	2.204473	56.094811	57.744659
Test 01	FQ	11:36:06	11:38:46	2.790691	18.037202	21.794952
Test 02	FQ	09:45:39	09:47:38	2.109832	77.162685	146.308467
Test 03	FQ	12:52:06	12:53:36	2.198268	47.667002	53.037932

Fig: Average Pupil Dilation, Left blink rate and right blink rate during HADS, STAI, BFI, FQ over 3 sessions for one Participant

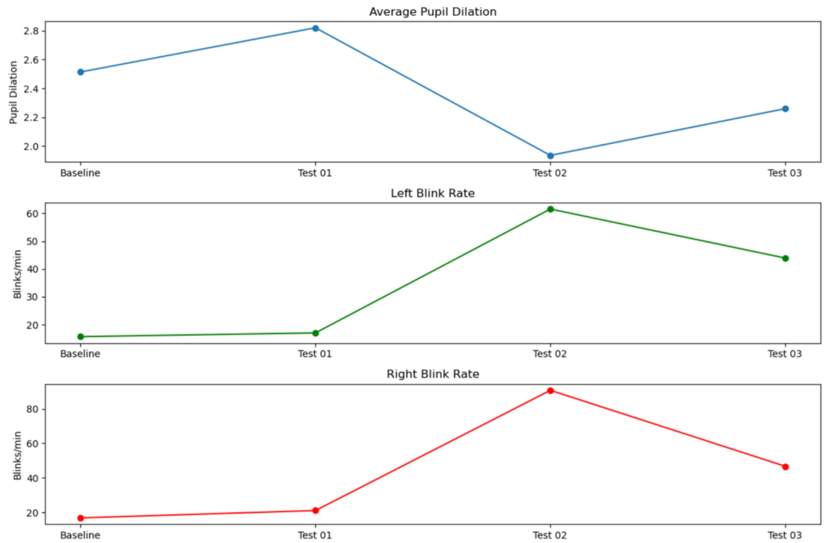


Fig: The graph shows that pupil dilation peaked in Test 01, and blink rates spiked in Test 02, indicating increased cognitive load or stress during these sessions, with both metrics decreasing in Test 03.

The standard deviation of pupil dilation for each participant across three sessions shows a variety of trends, indicating differences in physiological response patterns over time. Participants such as P01, P02, P07, and P08 exhibit higher variability in pupil dilation in Session 01, which tends to decrease in session 02 and session 03, suggesting a possible habituation effect as they become more known to the testing conditions. On the other hand, participants like P03, P04, and P09 show more stable or fluctuating variability, with no clear decreasing trends, indicating individual differences in physiological responses. Participants P06 and P10 have relatively low variability across all the sessions, showing consistent physiological responses. Overall, the data suggests that while some participants demonstrate reduced physiological variability over time, others maintain or fluctuate in their response patterns, reflecting individual differences in adaptation to the testing environment.

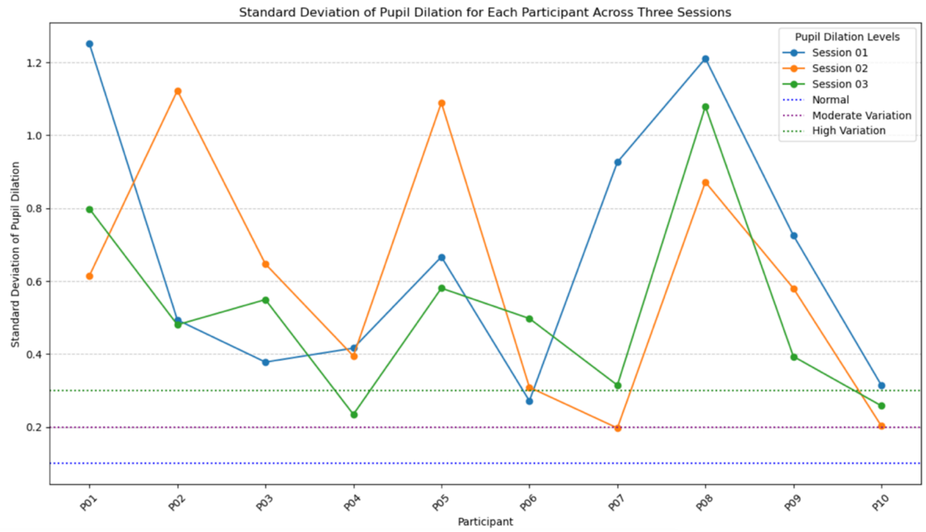


Fig: Pupil Dilation of 10 participants over 3 sessions

3.1.4 Heart-rate Metrics Analysis

Compared to the baseline average HR of 63.43 BPM, Test 01 shows a mild increase (64.5 - 67.2 BPM), indicating initial physiological arousal. Test 02 maintains a marginally higher HR (64.1 - 65.1 BPM), reflecting sustained engagement or stress. Test 03 exhibits a substantial rise in HR (84.9 - 87.1 BPM), indicating heightened anxiety or cognitive load.

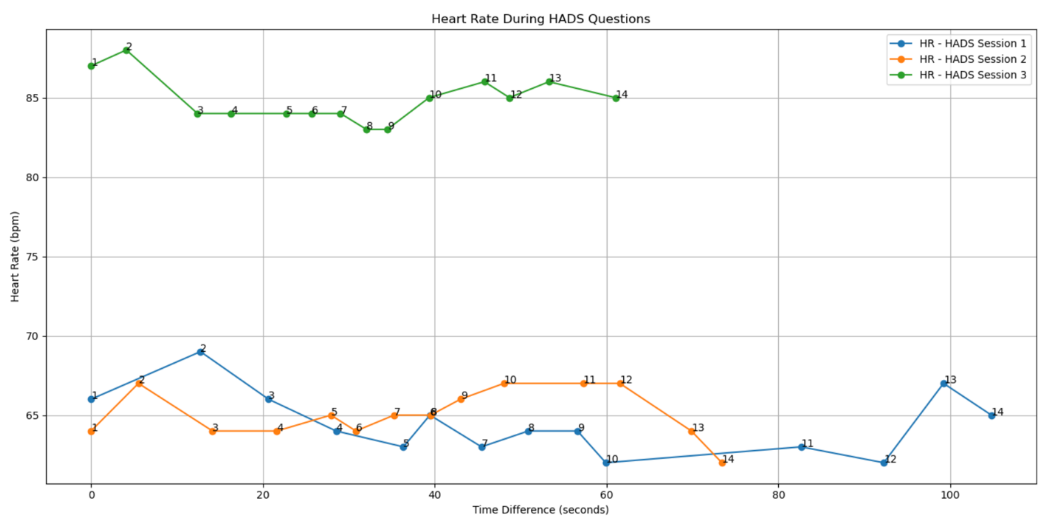


Fig: HR question by question change during HADS psychometric test

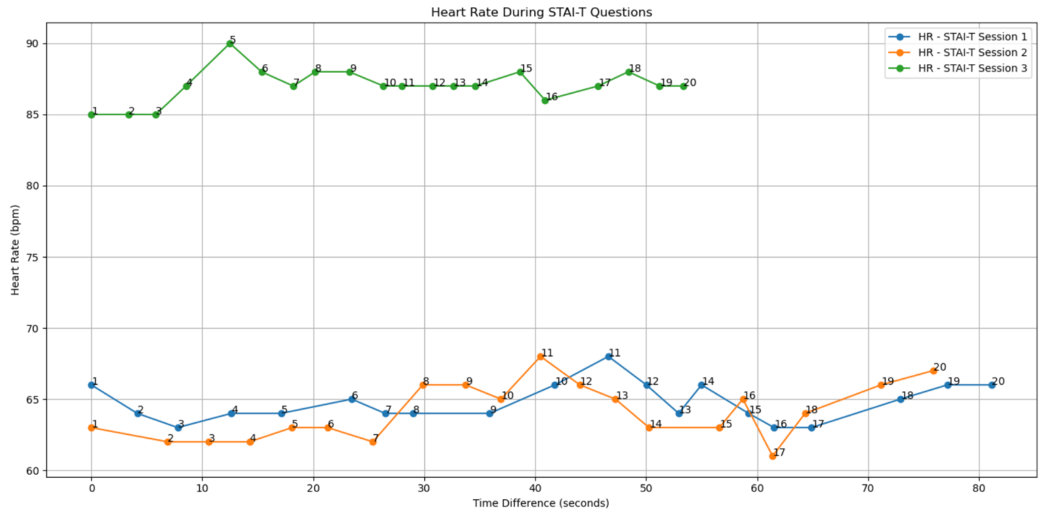


Fig: HR question by question change during STAI-T psychometric test

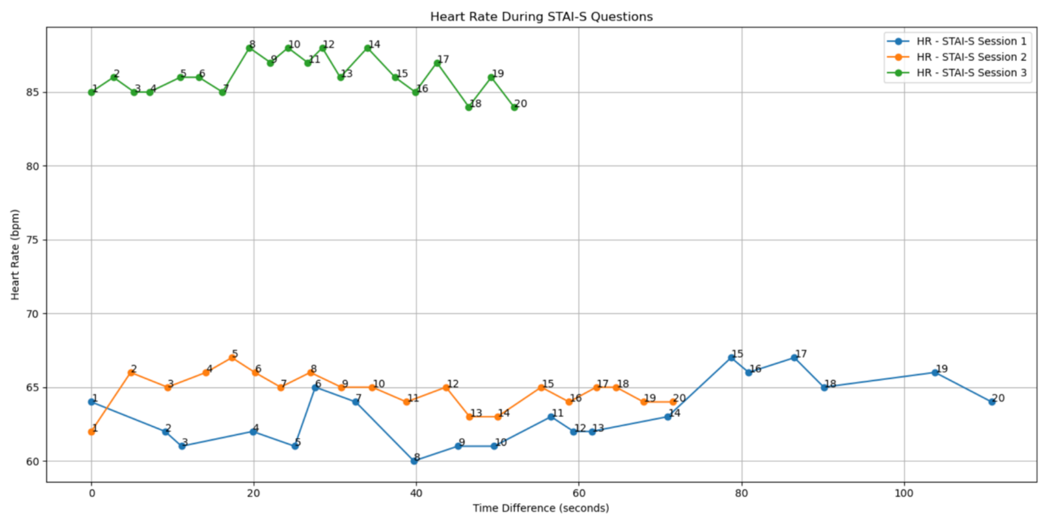


Fig: HR question by question change during STAI-S psychometric test

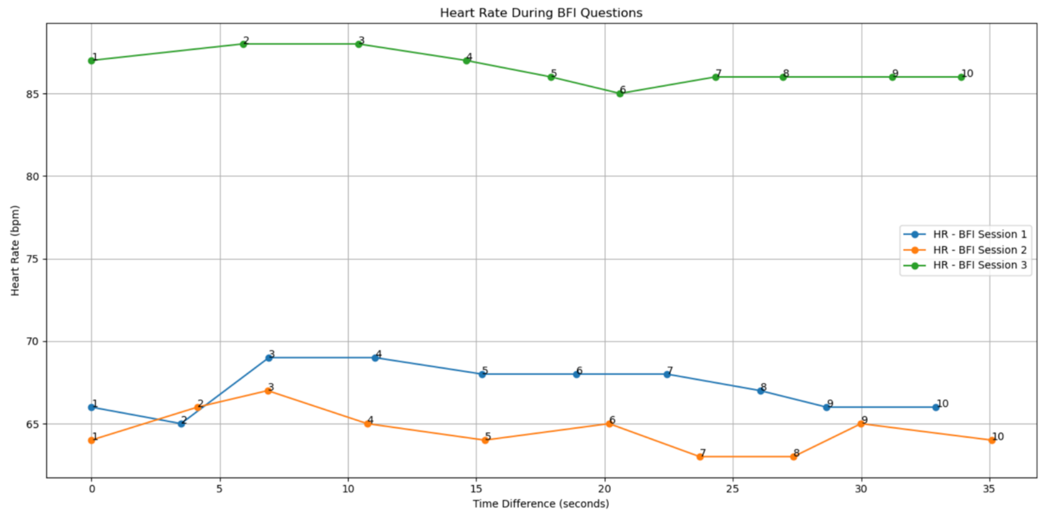


Fig: HR question by question change during BFI psychometric test

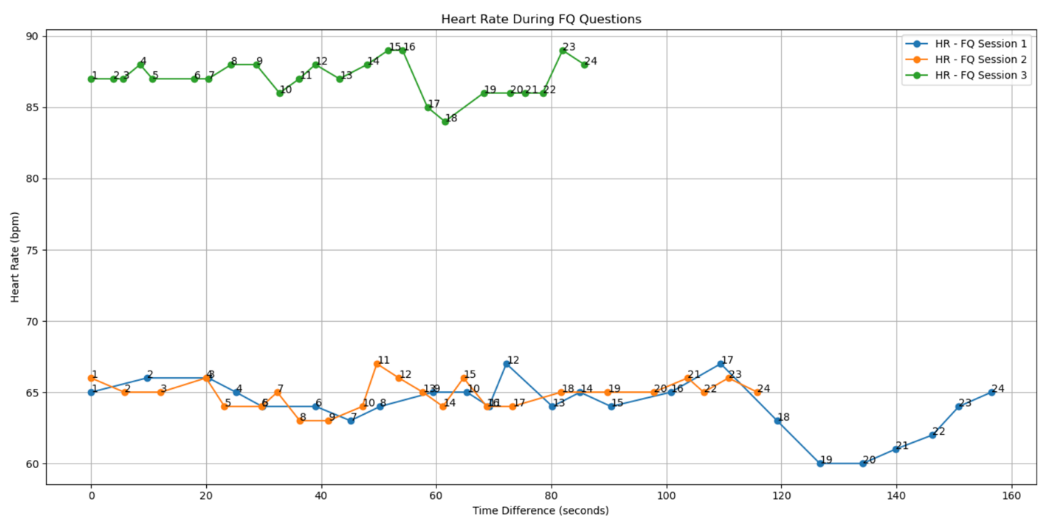


Fig: HR question by question change during FQ psychometric test

```
Baseline Average HR: 63.43 BPM

  Test    Type Start Time End Time  Average HR (BPM)
Test 1    HADS   11:30:18 11:32:10         64.500000
Test 2    HADS   09:41:08 09:42:25         65.071429
Test 3    HADS   12:48:35 12:49:38         84.857143
Test 1  STAI-S   11:32:10 11:34:04         63.300000
Test 2  STAI-S   09:42:25 09:43:40         64.750000
Test 3  STAI-S   12:49:38 12:50:32         86.100000
Test 1  STAI-T   11:34:04 11:35:30         64.750000
Test 2  STAI-T   09:43:40 09:45:00         64.100000
Test 3  STAI-T   12:50:32 12:51:30         87.050000
Test 1     BFI   11:35:30 11:36:06         67.200000
Test 2     BFI   09:45:00 09:45:39         64.600000
Test 3     BFI   12:51:30 12:52:06         86.500000
Test 1      FQ   11:36:06 11:38:46         64.083333
Test 2      FQ   09:45:39 09:47:38         64.916667
Test 3      FQ   12:52:06 12:53:36         87.083333
```

Fig: Average HR during HADS, STAI, BFI, FQ over 3 sessions for one Participant

Heart Rate Variability (HRV)

The HRV analysis reveals that compared to the baseline RMSSD of 48.31 ms and SDNN of 41.56 ms, Test 01 and Test 02 show moderate anxiety with slightly lower HRV metrics, while Test 03 exhibits significant anxiety with RMSSD and SDNN values well below both individual and general thresholds (e.g., HADS Test 03: RMSSD 22.71 ms, SDNN 17.77 ms). These findings validate the hypothesis that neurophysiological responses correlate with psychometric assessments and support the use of HRV metrics as reliable markers for identifying heightened anxiety and stress, enhancing the accuracy of psychological state evaluations.

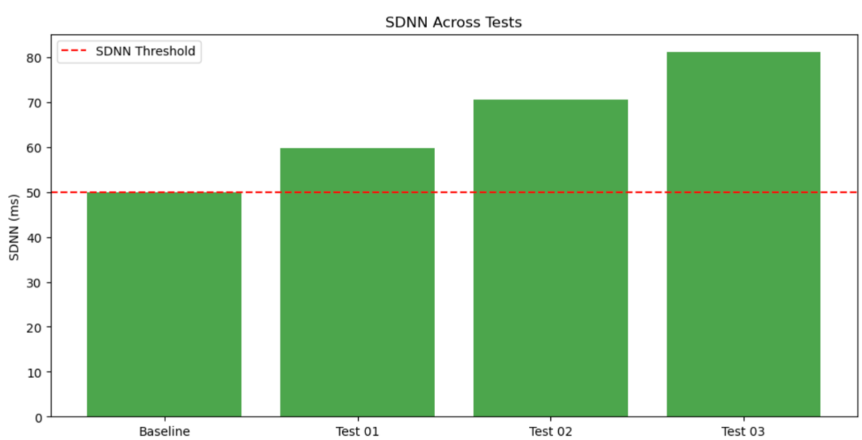


Fig: Average HRV (SDNN) during 3 sessions for one Participant

```
Baseline RMSSD: 48.31 ms, SDNN: 41.56 ms

   Test   Type Start Time End Time     RMSSD      SDNN
Test 01   HADS   11:30:18 11:32:10 42.152300 36.678218
Test 02   HADS   09:41:08 09:42:25 58.398769 46.822467
Test 03   HADS   12:48:35 12:49:38 22.708653 17.772358
Test 01 STAI-S   11:32:10 11:34:04 39.239574 35.556162
Test 02 STAI-S   09:42:25 09:43:40 38.275918 29.164953
Test 03 STAI-S   12:49:38 12:50:32 20.454531 15.703300
Test 01 STAI-T   11:34:04 11:35:30 37.230551 29.103002
Test 02 STAI-T   09:43:40 09:45:00 48.603887 41.662568
Test 03 STAI-T   12:50:32 12:51:30 16.705877 12.521043
Test 01    BFI   11:35:30 11:36:06 34.820558 28.794955
Test 02    BFI   09:45:00 09:45:39 41.972364 30.851403
Test 03    BFI   12:51:30 12:52:06 14.020424 11.863775
Test 01     FQ   11:36:06 11:38:46 52.289657 41.519129
Test 02     FQ   09:45:39 09:47:38 35.515305 25.736191
Test 03     FQ   12:52:06 12:53:36 15.479360 11.862604
```

Fig: Average HRV during HADS, STAI, BFI, FQ over 3 sessions for one Participant

3.1.5 Correlation Analysis

The correlation analysis visualizes the relationships between HRV (Heart Rate Variability) SDNN and pupil dilation standard deviation (STD) across three sessions for the 10 participants. Here are the key observations:

Strong Positive Correlations:

- **HRV_SDNN-Session 01 and Pupil_STD-Session 03 (0.85):** This indicates a strong positive correlation, suggesting that participants with higher HRV variability in Session 01 also tend to have higher pupil dilation variability in Session 03.
- **HRV_SDNN-Session 01 and Pupil_STD-Session 01 (0.64):** This strong positive correlation suggests a close relationship between HRV and pupil dilation variability within the same session.
- **HRV_SDNN-Session 03 and Pupil_STD-Session 01 (0.55):** Another strong positive correlation indicating a significant relationship between HRV variability in Session 03 and pupil dilation variability in Session 01.
- **Pupil_STD-Session 01 and Pupil_STD-Session 03 (0.68):** This suggests a strong positive correlation between pupil dilation variability in Session 01 and Session 03, indicating consistent physiological responses across these sessions.

Weak or Negative Correlations:

- **HRV_SDNN-Session 02 and Pupil_STD-Session 02 (-0.40):** This negative correlation suggests an inverse relationship between HRV variability and pupil dilation variability within Session 02.
- **HRV_SDNN-Session 02 and Pupil_STD-Session 01 (-0.16):** This weak negative correlation indicates a slight inverse relationship between HRV variability in Session 02 and pupil dilation variability in Session 01.

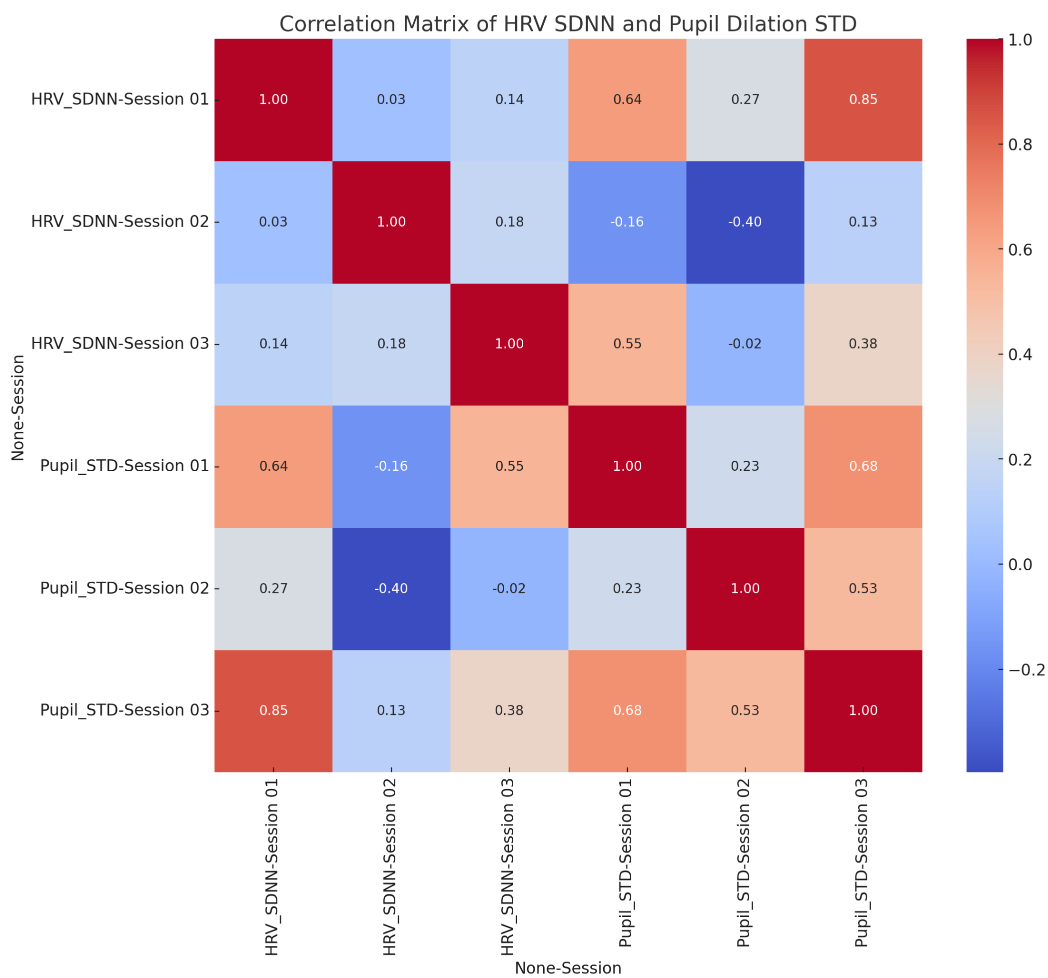


Fig: Correlation Analysis (Heatmap of HRV and Pupil Dilation)

The correlation analysis shows that there is generally a stronger relationship between HRV SDNN and pupil dilation STD within and across the sessions, particularly between Session 01 and Session 03. This indicates that participants who shows higher variability in heart rate tends to also show higher variability in pupil dilation, reflecting a consistent physiological response. The variability in correlation strengths across sessions suggests that the relationship between HRV and the pupil dilation may be influenced by session-specific factors.

3.2 Discussion

Integrating multimodal sensor data with traditional psychometric tests enhances the accuracy and objectivity of anxiety and depression assessments. Currently in the first prototype stage, we are continuously updating our software for better data synchronization. A limitation of our project is the reliance on prototype hardware, which may affect the consistency and reliability of data, highlighting the need for further refinement and validation of the equipment. We initially aimed to use four sensors—eye-tracking, face movement, skin conductance, and HRV but faced availability issues with skin conductance and lack of time to integrate face movement. We started with the available sensors, building this project from the beginning in a short amount of time.

By utilizing multimodal data from eye-tracking and heart rate variability sensors, the study provides a more comprehensive and objective evaluation of anxiety and depression. Furthermore, the implementation of advanced sensor technology and multimodal approaches can facilitate earlier detection of these conditions.

The high interindividual variability and low intraindividual variability observed in the group results suggest that while individual participants maintain consistent responses across sessions, there are significant differences between participants. This highlights the need for personalized assessment and more complete diagnostic strategies in psychological assessments. The stable responses within individuals indicate reliable measurement tools, but the considerable differences between individuals suggests the importance of having a personalized approach to effectively address the diverse psychological profiles of different participants. This dual finding supports the implementation of multimodal approaches and suggests further investigation and analysis into the factors contributing to interindividual differences.

The study explores the relationship between self-reported anxiety and depression and their physiological correlates, explored through both group-level analyses and individual case studies. The findings contribute to the broader understanding of the complex relationship between psychological states and physiological responses, making the way for more personalized strategies in anxiety and depression diagnosis. With this multimodal approach it might help address issues linked with the limitations of self-reports such as underdiagnosed and misdiagnosed anxiety and depression cases.

Further work in this area should focus on refining the prototype hardware to enhance data consistency and reliability, as well as integrating additional sensors such as skin conductance and facial movement tracking. Expanding the sample size and including a more diverse participant pool would also strengthen the generalizability of the findings. Future studies could explore the long-term efficacy of using multimodal sensor data in clinical settings, assessing how these technologies can be seamlessly integrated into routine psychological assessments. Additionally, developing more sophisticated machine learning models to analyze the comprehensive datasets could improve the predictive accuracy for anxiety and depression, paving the way for personalized and early intervention strategies in mental health care.

Chapter 4: Bibliography

Ancis, J. R. (2020). The age of cyberpsychology: An overview. Technology, Mind, and Behavior, 1(1). https://doi.org/10.1037/tmb0000009

Baig, M. Z., & Kavakli, M. (2019). A survey on psycho-physiological analysis & measurement methods in multimodal systems. Multimodal Technologies and Interaction, 3(2), 37.

Caponnetto, P., & Milazzo, M. (2019). Cyber Health Psychology: The use of new technologies at the service of psychological well-being and health empowerment. Health psychology research, 7(2).

Patrick, C. J., Iacono, W. G., & Venables, N. C. (2019). Incorporating neurophysiological measures into clinical assessments: Fundamental challenges and a strategy for addressing them. Psychological Assessment, 31(12), 1512.

Trigona, C., Graziani, S., & Baglio, S. (2020). Changes in sensors technologies during the last ten years: Evolution or revolution? IEEE Instrumentation & Measurement Magazine, 23(6), 18-22.

Johnson, L., & Roberts, M. (2018). Heart rate variability as a biomarker for anxiety disorder outcomes. Psychophysiology, 55(5), e13034.

Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health, 5, 258.

Green, T., & Harlow, E. (2021). Eye-tracking in anxiety disorders: A focus on fixation patterns. Journal of Anxiety Disorders, 73, 102233.

Bennett, F., & Young, R. (2017). Pupil dilation responses to emotional stimuli in normal and anxiety populations. Journal of Psychiatric Research, 95, 113-119.

Meo, M. M., Iaconis, F. R., Del Punta, J. A., Delrieux, C. A., & Gasaneo, G. (2024). Multifractal information on reading eye tracking data. Physica A: Statistical Mechanics and its Applications, 638, 129625.

Johnson, L., & Roberts, M. (2018). Heart rate variability as a biomarker for anxiety disorder outcomes. Psychophysiology, 55(5), e13034.

Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health, 5, 258.

Green, T., & Harlow, E. (2021). Eye-tracking in anxiety disorders: A focus on fixation patterns. Journal of Anxiety Disorders, 73, 102233.

Bennett, F., & Young, R. (2017). Pupil dilation responses to emotional stimuli in normal and anxiety populations. Journal of Psychiatric Research, 95, 113-119.

Fan, C., Chen, M., Wang, X., & Wang, J. (2021). A review on data preprocessing techniques toward efficient and reliable knowledge discovery from building operational data. *Frontiers in Energy Research*, 9. https://doi.org/10.3389/fenrg.2021.652801

Ehinger, B. V. (2021). Regression-based analysis of combined EEG and eye-tracking data: Theory and applications. Journal of Vision, 21(1), 3. https://doi.org/10.1167/jov.21.1.3

Axis Communications. (n.d.). AXIS P1275 Network Camera - Product support. Retrieved June 30, 2024, from https://www.axis.com/products/axis-p1275/support

Shorey, S., Ng, E. D., & Wong, C. H. (2022). Global prevalence of depression and elevated depressive symptoms among adolescents: A systematic review and meta-analysis. *British Journal of Clinical Psychology*, *61*(2), 287-305.

Trigona, C., Graziani, S., & Baglio, S. (2020). Changes in sensors technologies during the last ten years: Evolution or revolution?. *IEEE Instrumentation & Measurement Magazine*, *23*(6), 18-22.

Lan, G., Heit, B., Scargill, T., & Gorlatova, M. (2020). GazeGraph: graph-based few-shot cognitive context sensing from human visual behavior. In SenSys '20: Proceedings of the 18th Conference on Embedded Networked Sensor Systems (pp. 422–435). https://doi.org/10.1145/3384419.3430774

Khan, H. U. D. A., Bajwa, U. I., Ratyal, N. I., Zhang, F., & Anwar, M. W. (2024). Deception detection in videos using the facial action coding system. Multimedia Tools and Applications. Advance online publication. https://doi.org/10.1007/s11042-024-19153-4

Dean, R. T., & Bailes, F. (2013). Using time series analysis to evaluate skin conductance during movement in piano improvisation. Psychology of Music, 43(1), Advance online publication. https://doi.org/10.1177/0305735613489917

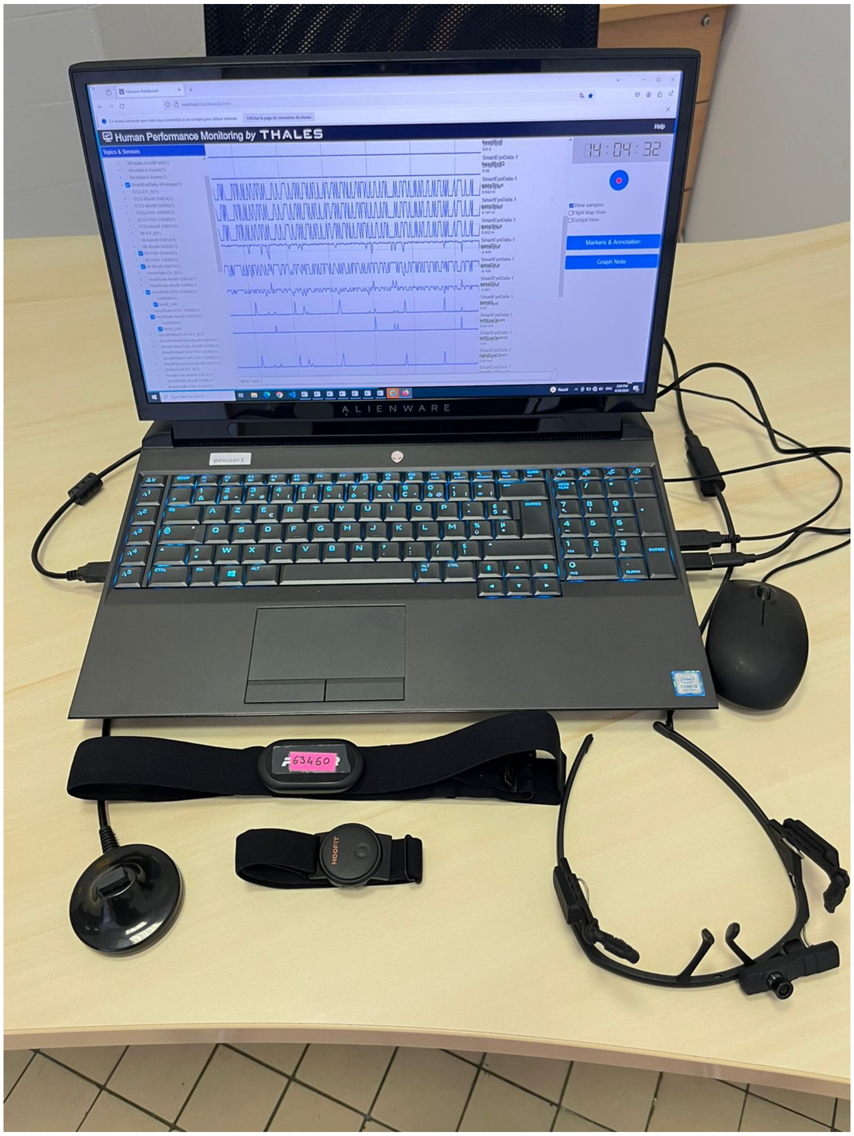
Basarkod, S., Valbrun, S., Wiltshire, C., France, J. M., Davie, W., Winters, S., George, S. A., Stenson, A. F., & Jovanovic, T. (2024). Prospective measurement of skin conductance response during trauma interview predicts future PTSD severity in trauma-exposed children. Journal of Mood & Anxiety Disorders, 7, 100061. https://doi.org/10.1016/j.jmood.2024.100061

Burma, J. S., Griffiths, J. K., Lapointe, A. P., Oni, I. K., Soroush, A., Carere, J., Smirl, J. D., & Dunn, J. F. (2024). Heart Rate Variability and Pulse Rate Variability: Do Anatomical Location and Sampling Rate Matter? Sensors, 24(7), 2048. https://doi.org/10.3390/s24072048

Ihianle, I. K., Machado, P., Owa, K., Adama, D. A., Otuka, R., & Lotfi, A. (2024). Minimizing redundancy, maximising relevance: HRV feature selection for stress classification. Expert Systems with Applications, 239, 122490. https://doi.org/10.1016/j.eswa.2023.122490

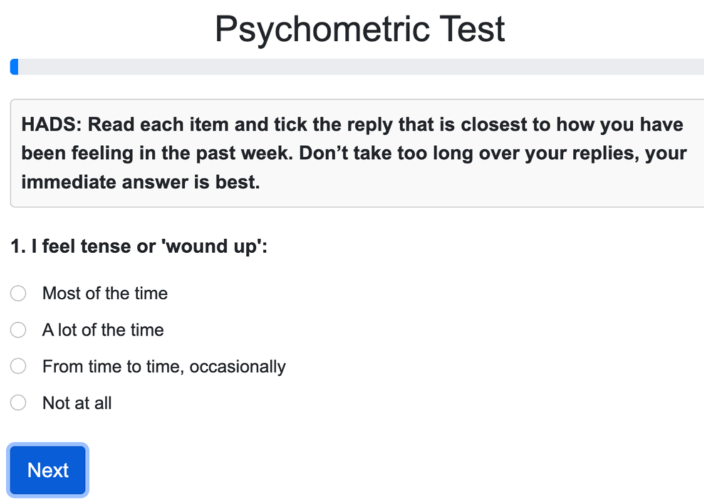
Chapter 5: Annex

Annex A. Multi-Sensors Setup

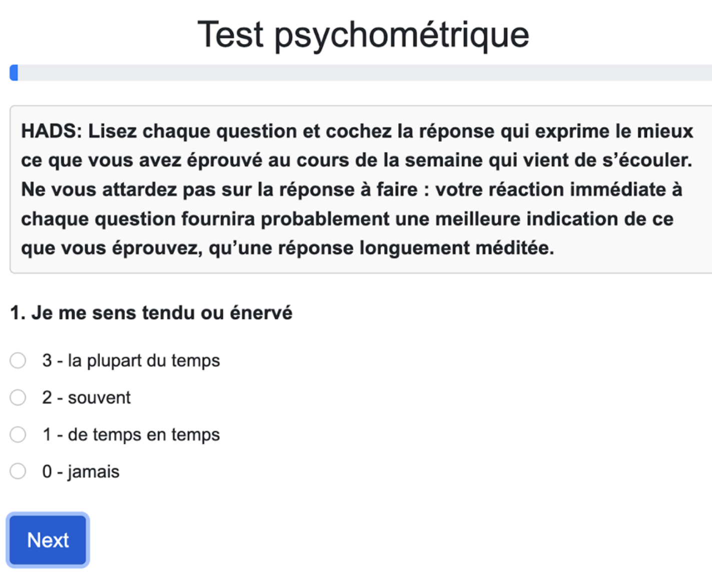


Annex B. Psychometric Test Software

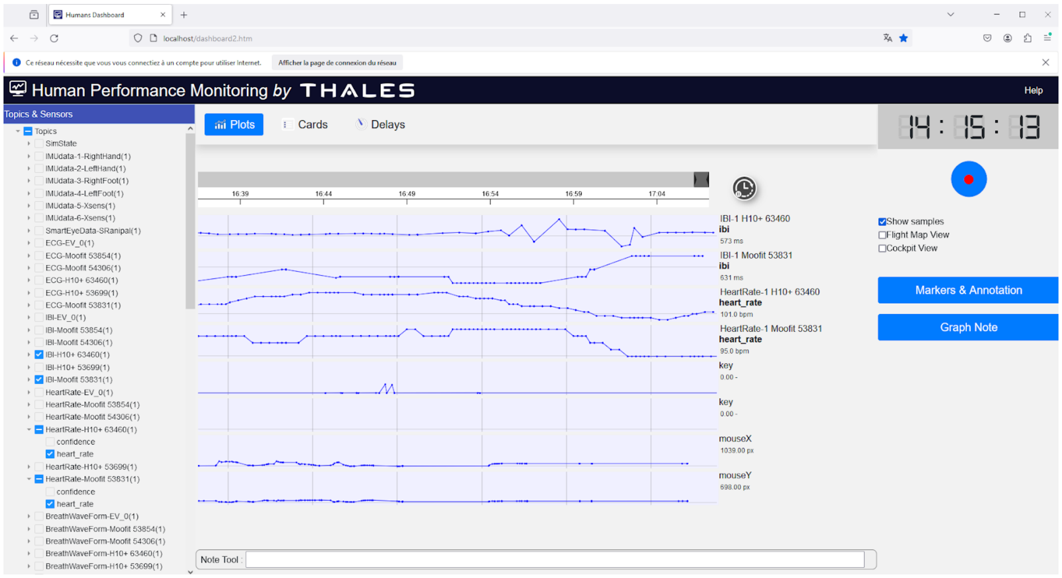
1. English Version



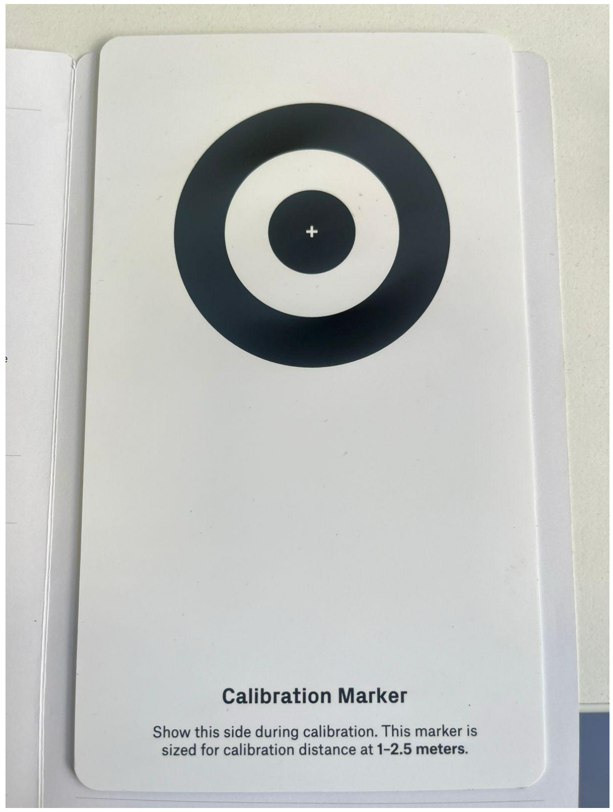
2. French Version

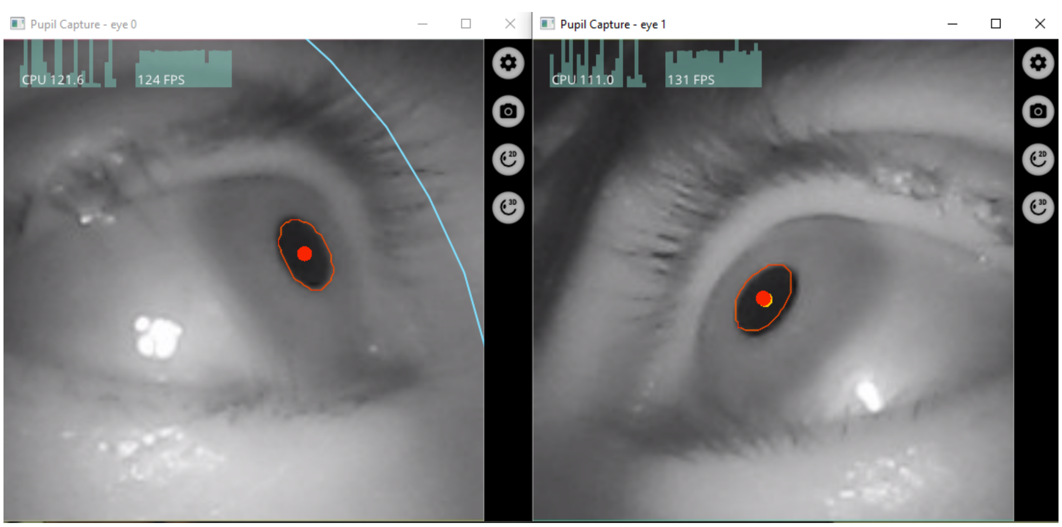


Annex C. Thales Human Performance Monitoring for Data Collection



Annex D. Eye-Tracking configuration and calibration





Annex E. Data Collection Season (Photo included with consent)

Annex F. Data Collection Season 02 (Photo included with consent)

Annex G. Psychometric Test Results

1. Summary Score

Summary Scores:
HADS Score:
- Anxiety: 7
- Depression: 7
STAI-S Score: 52
STAI-T Score: 47
BFI Score:
- Openness: 4
- Conscientiousness: 7
- Extraversion: 8
- Agreeableness: 6
- Neuroticism: 5
FQ Score:
- MainPhobia: 2
- TotalPhobia: 39
- Agoraphobia: 11
- BloodInjuryPhobia: 12
- SocialPhobia: 16
- GlobalPhobiaRating: 1
- AnxietyDepression: 12

2. Detailed Score

Detailed Responses:

Test: HADS
Question: 1. I feel tense or 'wound up':
Answer: From time to time, occasionally
Score: 1
Time: 4.103s
Question Start Time: 2024-06-24T12:48:35.382Z
Answer Time: 2024-06-24T12:48:39.486Z
Test: HADS
Question: 2. I still enjoy the things I used to enjoy:
Answer: Not quite so much
Score: 1
Time: 8.286s
Question Start Time: 2024-06-24T12:48:39.486Z
Answer Time: 2024-06-24T12:48:47.773Z
Test: HADS

Annex H. Dataset

1. Heart-rate dataset

hr_01.csv

Delimiter: ,

	reltime	datetime	iSensor	confidence	heart_rate
1	0.001	2024/06/13 11:30:10.5209	5	1.0	63.0
2	0.001	2024/06/13 11:30:10.5209	4	0.0	0.0
3	0.001	2024/06/13 11:30:10.5209	3	1.0	64.0
4	0.001	2024/06/13 11:30:10.5209	2	0.0	0.0
5	0.001	2024/06/13 11:30:10.5209	1	0.0	0.0
6	0.001	2024/06/13 11:30:10.5209	0	0.0	0.0
7	0.433	2024/06/13 11:30:10.9529	3	1.0	64.0
8	0.474	2024/06/13 11:30:10.9939	5	1.0	63.0
9	0.926	2024/06/13 11:30:11.4459	3	1.0	64.0
10	0.967	2024/06/13 11:30:11.4869	5	1.0	63.0
11	1.213	2024/06/13 11:30:11.7329	5	1.0	63.0
12	1.419	2024/06/13 11:30:11.9389	3	1.0	65.0
13	1.46	2024/06/13 11:30:11.9799	5	1.0	63.0
14	1.911	2024/06/13 11:30:12.4309	3	1.0	65.0
15	1.951	2024/06/13 11:30:12.4709	5	1.0	63.0
16	2.158	2024/06/13 11:30:12.6779	3	1.0	65.0
17	2.198	2024/06/13 11:30:12.7179	5	1.0	63.0
18	2.404	2024/06/13 11:30:12.9239	3	1.0	65.0
19	2.444	2024/06/13 11:30:12.9639	5	1.0	63.0
20	2.65	2024/06/13 11:30:13.1699	3	1.0	65.0
21	2.69	2024/06/13 11:30:13.2099	5	1.0	63.0
22	2.897	2024/06/13 11:30:13.4169	3	1.0	65.0
23	2.937	2024/06/13 11:30:13.4569	5	1.0	63.0

2. Eye-Tracking dataset

sed_01.csv

Delimiter: ,

	gazeSrc.z	gazeDir.x	gazeDir.y	gazeDir.z	gazeQ	leftEyeOpen	leftEyeOpenQ	rightEyeOpen	rightEyeOpenQ	pupil
1	-0.015	0.969	-0.186	0.162	0.99	10.0	1.0	9.75	1.0	3.53
2	-0.015	0.949	-0.192	0.25	1.0	10.0	1.0	10.0	1.0	3.19
3	-0.015	0.947	-0.198	0.252	1.0	10.0	1.0	10.0	1.0	3.21
4	-0.015	0.948	-0.197	0.251	1.0	10.0	1.0	10.0	1.0	3.2
5	-0.015	0.948	-0.197	0.252	1.0	10.0	1.0	10.0	1.0	3.19
6	-0.015	0.948	-0.196	0.25	1.0	10.0	1.0	10.0	1.0	3.2
7	-0.015	0.948	-0.194	0.251	1.0	10.0	1.0	10.0	1.0	3.22
8	-0.015	0.949	-0.195	0.249	1.0	10.0	1.0	10.0	1.0	3.22
9	-0.015	0.948	-0.194	0.252	1.0	10.0	1.0	10.0	1.0	3.25
10	-0.015	0.948	-0.194	0.252	1.0	10.0	1.0	10.0	1.0	3.24
11	-0.015	0.947	-0.196	0.254	1.0	10.0	1.0	10.0	1.0	3.23
12	-0.015	0.947	-0.195	0.255	1.0	10.0	1.0	10.0	1.0	3.2
13	-0.015	0.947	-0.194	0.255	1.0	10.0	1.0	10.0	1.0	3.22
14	-0.015	0.946	-0.197	0.257	1.0	10.0	1.0	10.0	1.0	3.22
15	-0.015	0.947	-0.197	0.255	1.0	10.0	1.0	10.0	1.0	3.2
16	-0.015	0.948	-0.192	0.256	1.0	10.0	1.0	10.0	1.0	3.2
17	-0.015	0.948	-0.192	0.256	1.0	10.0	1.0	10.0	1.0	3.2
18	-0.015	0.948	-0.191	0.255	1.0	10.0	1.0	10.0	1.0	3.21
19	-0.015	0.948	-0.191	0.255	1.0	10.0	1.0	10.0	1.0	3.21
20	-0.015	0.948	-0.188	0.256	1.0	10.0	1.0	10.0	1.0	3.18
21	-0.015	0.948	-0.189	0.255	1.0	10.0	1.0	10.0	1.0	3.2
22	-0.015	0.947	-0.193	0.257	1.0	10.0	1.0	10.0	1.0	3.17

3. Psychometric Test dataset

Psychometric_Test_Results

Delimiter: ,

	Psychometric Tests	Question	Answer	Score	Time(s)	Question Start Time	Question Answer Time	Anxiety Question
1	HADS	1. I feel tense or 'wound up':	From time to time; occasionally	1	9.551	2024-06-06T13:41:54.041Z	2024-06-06T13:42:03.593Z	Anxiety
2	HADS	2. I still enjoy the things I used to enjoy:	Definitely as much	0	7.984	2024-06-06T13:42:03.593Z	2024-06-06T13:42:11.577Z	
3	HADS	g as if something awful is about to happen:	Not at all	0	7.599	2024-06-06T13:42:11.577Z	2024-06-06T13:42:19.176Z	Anxiety
4	HADS	can laugh and see the funny side of things:	As much as I always could	0	8.136	2024-06-06T13:42:19.176Z	2024-06-06T13:42:27.312Z	
5	HADS	5. Worrying thoughts go through my mind:	From time to time; but not too often	1	6.024	2024-06-06T13:42:27.312Z	2024-06-06T13:42:33.336Z	Anxiety
6	HADS	6. I feel cheerful:	Sometimes	1	5.512	2024-06-06T13:42:33.336Z	2024-06-06T13:42:38.848Z	
7	HADS	7. I can sit at ease and feel relaxed:	Usually	1	10.889	2024-06-06T13:42:38.848Z	2024-06-06T13:42:49.737Z	Anxiety
8	HADS	8. I feel as if I am slowed down:	Sometimes	1	16.583	2024-06-06T13:42:49.737Z	2024-06-06T13:43:06.320Z	
9	HADS	ɘned feeling like 'butterflies' in the stomach:	Not at all	0	16.952	2024-06-06T13:43:06.320Z	2024-06-06T13:43:23.272Z	Anxiety
10	HADS	10. I have lost interest in my appearance:	I take just as much care as ever	0	9.096	2024-06-06T13:43:23.272Z	2024-06-06T13:43:32.368Z	
11	HADS	I feel restless as I have to be on the move:	Not very much	1	17.384	2024-06-06T13:43:32.368Z	2024-06-06T13:43:49.752Z	Anxiety
12	HADS	12. I look forward with enjoyment to things:	Rather less than I used to	1	15.432	2024-06-06T13:43:49.752Z	2024-06-06T13:44:05.184Z	
13	HADS	13. I get sudden feelings of panic:	Not very often	1	4.688	2024-06-06T13:44:05.184Z	2024-06-06T13:44:09.872Z	Anxiety
14	HADS	enjoy a good book or radio or TV program:	Sometimes	1	10.777	2024-06-06T13:44:09.872Z	2024-06-06T13:44:20.649Z	
15	STAI-S	1. I feel calm.	Very much	1	12.424	2024-06-06T13:44:20.649Z	2024-06-06T13:44:33.073Z	Anxiety
16	STAI-S	2. I feel secure.	Somewhat	3	5	2024-06-06T13:44:33.073Z	2024-06-06T13:44:38.073Z	Anxiety
17	STAI-S	3. I am tense.	Somewhat	2	11.111	2024-06-06T13:44:38.073Z	2024-06-06T13:44:49.184Z	Anxiety
18	STAI-S	4. I feel regretful.	Not at all	1	3.112	2024-06-06T13:44:49.184Z	2024-06-06T13:44:52.296Z	Anxiety
19	STAI-S	5. I feel at ease.	Somewhat	3	12.128	2024-06-06T13:44:52.296Z	2024-06-06T13:45:04.424Z	Anxiety
20	STAI-S	6. I feel upset.	Not at all	1	3.008	2024-06-06T13:45:04.424Z	2024-06-06T13:45:07.432Z	Anxiety
21	STAI-S	ırrently worried about possible misfortunes.	Not at all	1	4	2024-06-06T13:45:07.432Z	2024-06-06T13:45:11.432Z	Anxiety
22	STAI-S	8. I feel rested.	Somewhat	3	6.408	2024-06-06T13:45:11.432Z	2024-06-06T13:45:17.840Z	Anxiety
23	STAI-S	9. I feel anxious.	Not at all	1	7.824	2024-06-06T13:45:17.840Z	2024-06-06T13:45:25.664Z	Anxiety

Annex I. Data Analysis for Duration

jupyter Time Last Checkpoint: 1 minute ago

File Edit View Run Kernel Settings Help Trusted

Code · Open in... Python 3 (ipykernel)

[16]:

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the datasets
psychometric_01 = pd.read_csv('/Users/urmebose/Desktop/People/Nuro/Psychometric_Test_Results_01.csv')
psychometric_02 = pd.read_csv('/Users/urmebose/Desktop/People/Nuro/Psychometric_Test_Results_02.csv')
psychometric_03 = pd.read_csv('/Users/urmebose/Desktop/People/Nuro/Psychometric_Test_Results_03.csv')

# Convert datetime columns to datetime objects
psychometric_01['Question Start Time'] = pd.to_datetime(psychometric_01['Question Start Time']).dt.tz_localize(None)
psychometric_02['Question Start Time'] = pd.to_datetime(psychometric_02['Question Start Time']).dt.tz_localize(None)
psychometric_03['Question Start Time'] = pd.to_datetime(psychometric_03['Question Start Time']).dt.tz_localize(None)

psychometric_01['Question Answer Time'] = pd.to_datetime(psychometric_01['Question Answer Time']).dt.tz_localize(None)
psychometric_02['Question Answer Time'] = pd.to_datetime(psychometric_02['Question Answer Time']).dt.tz_localize(None)
psychometric_03['Question Answer Time'] = pd.to_datetime(psychometric_03['Question Answer Time']).dt.tz_localize(None)

# Calculate the answer duration for each session
psychometric_01['answer_duration'] = (psychometric_01['Question Answer Time'] - psychometric_01['Question Start Time']).dt.total_seconds() / 6
psychometric_02['answer_duration'] = (psychometric_02['Question Answer Time'] - psychometric_02['Question Start Time']).dt.total_seconds() / 6
psychometric_03['answer_duration'] = (psychometric_03['Question Answer Time'] - psychometric_03['Question Start Time']).dt.total_seconds() / 6

psychometric_01['Session'] = 'Session 01'
psychometric_02['Session'] = 'Session 02'
psychometric_03['Session'] = 'Session 03'

all_sessions = pd.concat([psychometric_01, psychometric_02, psychometric_03])

session_stats = all_sessions.groupby('Session')['answer_duration'].agg(['count', 'sum', 'std']).reset_index()
session_stats.rename(columns={'count': 'Count', 'sum': 'Total Timing (minutes)', 'std': 'Standard Deviation (minutes)'}, inplace=True)

# Display the results
print("Total Timing During 3 Sessions")
print(session_stats)

# Plot the answer duration for each session
plt.figure(figsize=(12, 6))
sns.boxplot(data=all_sessions, x='Session', y='answer_duration')
plt.title('Comparison of Answer Duration Across Sessions')
plt.ylabel('Answer Duration (minutes)')
plt.xlabel('Session')
plt.show()
```

Annex J. Data Analysis for Pupil Dilation

```
import pandas as pd

file_path = '/Users/urmebose/Desktop/People/Nuro/sed.csv'
baseline_eye_tracking = pd.read_csv(file_path)

baseline_eye_tracking.rename(columns={
    'datetime': 'timestamp',
    'pupil': 'pupil_dilation',
    'leftEyeOpen': 'left_blink',
    'rightEyeOpen': 'right_blink'
}, inplace=True)


baseline_eye_tracking['timestamp'] = pd.to_datetime(baseline_eye_tracking['timestamp'], errors='coerce').dt.tz_localize(None)
baseline_eye_tracking = baseline_eye_tracking.dropna(subset=['timestamp'])

# start and end times
start_time = baseline_eye_tracking['timestamp'].min()
end_time = baseline_eye_tracking['timestamp'].max()

# Calculate the total duration
total_duration_seconds = (end_time - start_time).total_seconds()
total_duration_minutes = total_duration_seconds / 60

# Calculate average pupil dilation
average_pupil_dilation = baseline_eye_tracking['pupil_dilation'].mean()

# Threshold to detect potential blinks
blink_detection_threshold = 1.0


# Detect potential blinks
left_blink_count = ((baseline_eye_tracking['left_blink'] > blink_detection_threshold) &
                    (baseline_eye_tracking['left_blink'].shift(-1) <= blink_detection_threshold)).sum()

right_blink_count = ((baseline_eye_tracking['right_blink'] > blink_detection_threshold) &
                     (baseline_eye_tracking['right_blink'].shift(-1) <= blink_detection_threshold)).sum()

# Calculate blink rate per minute
left_blink_rate = left_blink_count / total_duration_minutes
right_blink_rate = right_blink_count / total_duration_minutes

# Display the results clearly
print(f"Baseline Metrics:\n")
print(f"  Start Time: {start_time}")
print(f"  End Time: {end_time}")
print(f"  Total Duration: {total_duration_minutes:.2f} minutes")
print(f"  Average Pupil Dilation: {average_pupil_dilation:.2f}")
print(f"  Left Blink Rate: {left_blink_rate:.2f} blinks/min")
print(f"  Right Blink Rate: {right_blink_rate:.2f} blinks/min")
```

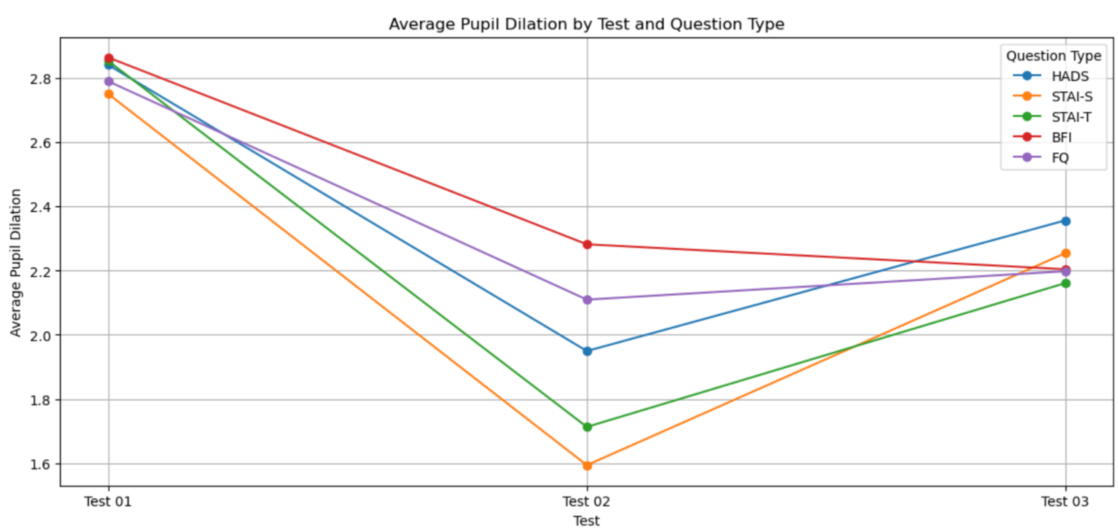
```
Baseline Metrics:

  Start Time: 2024-06-05 10:44:55.920900
  End Time: 2024-06-05 10:46:42.806900
  Total Duration: 1.78 minutes
  Average Pupil Dilation: 2.51
  Left Blink Rate: 15.72 blinks/min
  Right Blink Rate: 16.84 blinks/min
```

Annex K. Data Analysis for HRV

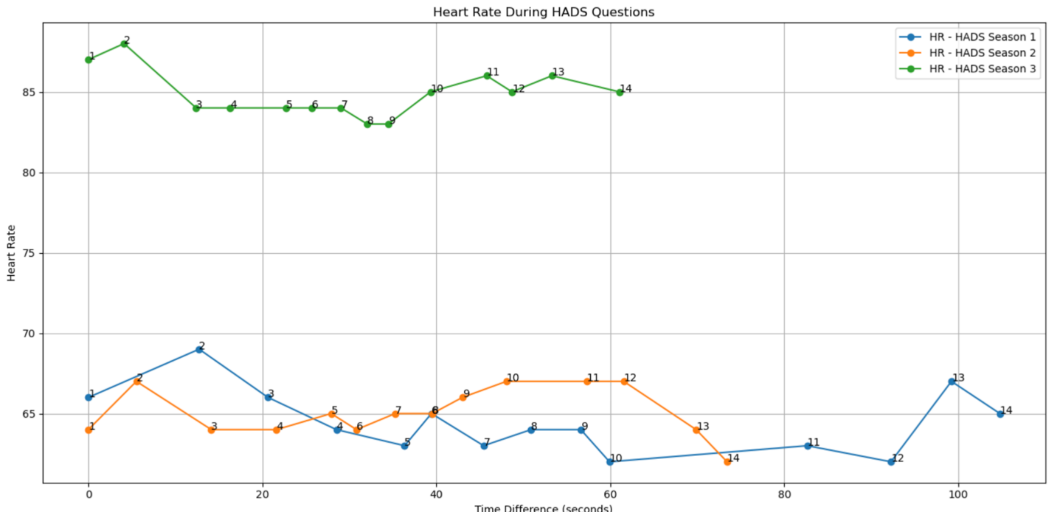
```
import pandas as pd
import numpy as np

ibi_baseline = pd.read_csv('/Users/urmebose/Desktop/People/Nuro/ibi.csv')
ibi_01 = pd.read_csv('/Users/urmebose/Desktop/People/Nuro/ibi_01.csv')
ibi_02 = pd.read_csv('/Users/urmebose/Desktop/People/Nuro/ibi_02.csv')
ibi_03 = pd.read_csv('/Users/urmebose/Desktop/People/Nuro/ibi_03.csv')

def calculate_hrv_metrics(ibi_data):
    if 'ibi' in ibi_data.columns:
        valid_ibi = ibi_data[ibi_data['ibi'] > 0]['ibi']

        diff_nn_intervals = np.diff(valid_ibi)  # Calculate differences between successive NN intervals
        squared_diffs = np.square(diff_nn_intervals)  # Square the differences
        rmssd = np.sqrt(np.mean(squared_diffs))  # Root mean square of the differences gives RMSSD
        sdnn = np.std(valid_ibi, ddof=1)  # Standard deviation of NN intervals

        return rmssd, sdnn
    else:
        print("IBI data column not found. Please ensure the HR data includes 'ibi' measurements.")
        return None, None

rmssd_baseline, sdnn_baseline = calculate_hrv_metrics(ibi_baseline)
rmssd_01, sdnn_01 = calculate_hrv_metrics(ibi_01)
rmssd_02, sdnn_02 = calculate_hrv_metrics(ibi_02)
rmssd_03, sdnn_03 = calculate_hrv_metrics(ibi_03)

print(f"Baseline RMSSD: {rmssd_baseline:.2f} ms, SDNN: {sdnn_baseline:.2f} ms")
print(f"Test 01 RMSSD: {rmssd_01:.2f} ms, SDNN: {sdnn_01:.2f} ms")
print(f"Test 02 RMSSD: {rmssd_02:.2f} ms, SDNN: {sdnn_02:.2f} ms")
print(f"Test 03 RMSSD: {rmssd_03:.2f} ms, SDNN: {sdnn_03:.2f} ms")
```

```
Baseline RMSSD: 48.31 ms, SDNN: 41.56 ms
Test 01 RMSSD: 46.48 ms, SDNN: 39.46 ms
Test 02 RMSSD: 44.99 ms, SDNN: 35.51 ms
Test 03 RMSSD: 18.28 ms, SDNN: 15.34 ms
```

Annex L. Eye-tracking during Season 01, 02, 03



Annex M. HR during Season 01, 02, 03



Annex N. Machine Learning Modeling