ISSN: 2473-4901
v10 n6207

Evaluating Stress and Driving Performance Using VR and Physiological Data: A Case Study

Dr. Rehma Razzak
rrazzak@students.kennesaw.edu
College of Computing and Software Engineering
Kennesaw State University
Marietta, GA, 30060, USA

Dr. Yi (Joy) Li
yli49@kennesaw.edu
College of Computing and Software Engineering
Kennesaw State University
Marietta, GA, 30060, USA

Dr. Estate (Tato) Sokhadze
estate.sokhadze@duke.edu
Duke University School of Medicine
Department of Neurology
Durham, NC, 27710, USA

Dr. Jing (Selena) He
she4@kennesaw.edu
College of Computing and Software Engineering
Kennesaw State University
Marietta, GA, 30060, USA

Abstract

This project aimed to analyze biometric data from participants engaged in a Virtual Reality (VR) driving simulation to understand how gender influences physiological responses to driving stress. Utilizing statistical methods like mixed linear models, Autoregressive Integrated Moving Average (ARIMA) modeling, Mann-Whitney U tests, and quantile regression, we examined the metrics of electrodermal activity (EDA), pulse rate, and temperature. Our findings indicated significant gender-based differences in these biometric responses, with female participants showing more pronounced changes in EDA and temperature compared to their male counterparts. Participants also provided valuable feedback for improving the VR experience.

Keywords: Physiological Data, VR Driving Simulation, Gender Differences, Stress Responses, Driving Performance

 ISSN: 2473-4901
v10 n6207

1. INTRODUCTION

Driving is a complex activity involving cognitive and physical tasks, including visual and perceptual integration, decision making, vehicle control, and responding to dynamic environments (Caffò et al., 2020; Calvi et al., 2020). Learning to drive requires time and effort, and VR technology has emerged as a powerful tool to enhance this process. By simulating real-world experiences, VR helps new drivers grasp driving fundamentals in an engaging manner, increasing retention of critical information (Alonso et al., 2023). Additionally, VR simulators offer a safe, effective method for evaluating driving performance by integrating perceptual input, cognitive processing, and behavioral output, proving to be reliable and valid tools (Bédard et al., 2010; Davenne et al., 2012). Studies have also shown VR to be useful in examining driving behavior in various conditions, such as rural road intersections (Basu et al., 2022), and in assessing driver stress (Wickens et al., 2015).

Building on this, research has highlighted significant differences in driving behavior based on gender, which have implications for risk perception, traffic accident involvement, and driving performance. Studies indicate that female drivers often experience higher stress levels, and exhibit more pronounced physiological responses in stressful driving scenarios compared to men (Ferrante et al., 2019). For instance, female drivers tend to show lower HRV (Heart Rate Variability) under stress, indicating higher physiological stress levels that correlate with poorer driving outcomes (Arca et al., 2022). Additionally, women often report higher levels of stress and anxiety in driving situations, which leads to more significant physiological reactions such as increased heart rates and EDA Maxwell et al., 2021; Matthews et al., 1999).

Further evidence suggests that male and female drivers exhibit different behaviors during stopping maneuvers in urban environments, with men generally performing these maneuvers more carefully than women (De Blasiis et al., 2017). Driving simulator studies have also shown that female drivers are more likely to be involved in crashes due to errors in yielding, gap acceptance, and speed regulation (Ferrante et al., 2019). These findings highlight the importance of considering gender differences when designing and implementing VR driving simulations.

Incorporating these insights into VR driver training programs can enhance effectiveness by addressing specific stressors and tailoring interventions based on individual biometric profiles. Recognizing and accommodating the unique physiological and psychological responses of different genders can provide a more comprehensive training experience, ultimately contributing to safer driving practices.

As such, we implemented a VR driving game in address some of these findings. In our work, we attempt to address the following questions:

- RQ1: Were the participants less or more stressed as they played the VR Driving Game?
- RQ2: Which physiological metric was the most significant for the participants, and which were the most consistently statistically significant overall?
- RQ3: Were there any significant findings in terms of gender?
- RQ4: Did the VR Driving Game have a positive impact on the participants?

Section 2 of our paper discusses related works, while Section 3 details our experiment and VR driving game. Section 4 presents initial results from the participants' self-report questionnaires, and Section 5 covers data collection and preprocessing. Section 6 provides the analysis and results. Finally, Section 7 concludes the paper, and Section 8 discusses future work for our game.

2. RELATED LITERATURE

Using VR Driving Simulators to Measure Stress

Evaluating stress through physiological signals in a VR driving environment is a significant research area due to its profound impact on driving performance. Stress triggers physiological responses such as increased heart rate, elevated blood pressure, altered breathing patterns, and muscle tension, all of which can impair reaction time, decision-making, and overall driving performance (Keraustret et al., 2021).

In a VR driving environment, real-time monitoring and analysis of physiological responses provide valuable insights into how stress influences driving behavior. This understanding aids in developing interventions to manage stress, ultimately improving road safety (Antoun et al., 2017).

Building on this, a 2023 study by Mateos-García

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developed a system using biometric sensors in VR simulations to recognize driver stress. Using a PPG (Photoplethysmography) sensor, they found that heart rate closely correlates with stress levels, with ML (Machine Learning) algorithms classifying stress in real-time, demonstrating the feasibility of wearable devices for stress detection in driving scenarios (Mateos-García et al., 2023). Similarly, their 2022 study utilized PPG sensors to detect stress through HRV data, validated with VR experiments, further supporting the use of wearable devices for non-invasive stress detection (Mateos-García et al., 2022).

Expanding on this research, another study examined physiological responses such as GSR (Galvanic Skin Response), BVP (Blood Volume Pulse), and PR (Pupillary Response) in VR driving simulators. Testing 24 participants in five simulation environments revealed significant differences in GSR, highlighting how simulator environments affect stress levels. The study found that female participants exhibited higher stress levels, indicating gender as a crucial factor in physiological responses to driving simulations. Hybrid GA-SVM (Genetic Algorithm-Support Vector machine) and GA-ANN (Genetic Algorithm-Artificial Neural Network) approaches were used for data classification, providing insights into user engagement and stress responses (Liu et al., 2020).

Further exploring physiological responses, a study on individuals with ASD (Autism Spectrum Disorder) used EEG (Electroencephalography) data to classify affective states and mental workload during VR driving simulations. Twenty adolescents with ASD participated, with high classification accuracy achieved using k-nearest neighbors algorithm and univariate feature selection methods, supporting the feasibility of EEG-based models for recognizing affective states in driving contexts (Fan et al., 2018). Similar findings in earlier studies also found that other aspects, such as executive functioning and working memory, were noticeably worse in autistic individuals, and the incorporation of VR Driving simulations resulted in significant improvement (D.J Cox et al., 2017; S.M. Cox et al., 2015).

In the realm of therapeutic applications, a study on VR exposure therapy (VRET) for women with driving phobia demonstrated reduced anxiety and distorted thoughts after VRET sessions. Thirteen women participated and the findings suggested VRET can reduce anxiety and facilitate in vivo exposure for driving phobia without associated risks (Costa et al., 2018).

A cross-sectional study evaluated risky driving behavior across age groups using driving simulators. The sample included 115 drivers divided into young inexperienced (18-21 years), adult experienced (25-55 years), and older adult (70-86 years) groups. Participants were tested on scenarios with varying mental workloads. The study found that moderate scenario complexity highlighted differences in driving ability and elicited realistic behavior, with novel driving measures providing useful, non-redundant information (Michaels et al., 2017).

Investigating the impact of time pressure, one study involved 54 participants driving a 6.9-km urban track with and without time constraints. Measurements included driving performance, eye movement, pupil diameter, cardiovascular and respiratory activity. Under time pressure, participants drove faster, exhibited increased physiological activity, and altered their driving strategies. The findings emphasize the importance of managing stress to improve driving performance (Rendon-Velez et al., 2016).

Another study explored the relationship between flow states and HRV in driving simulations. Eighteen psychology students participated in tasks with varying demand levels to induce flow, anxiety, or boredom. HRV measures indicated that balanced skill-demand levels induced flow, while too high or low demands caused anxiety or boredom. The study demonstrates how VR environments can effectively investigate psychological states and their impact on physiological responses (Tozman et al., 2015).

Remarks

These studies collectively underscore the significant role of VR driving simulators and physiological data in understanding and managing stress in driving. Leveraging advanced methodology and tools, we can develop effective interventions to enhance driver safety and performance. The versatility and effectiveness of VR driving simulators in enhancing driving skills, assessing driver behavior, and improving traffic safety are well-established.

Despite progress, notable research gaps remain:

- Personalized Models: Many studies develop models that are personalized to the individual subjects in the study. While this can improve the accuracy of stress detection for those individuals, it comes at a cost of generalizability.

ISSN: 2473-4901
v10 n6207

- Realism of VR Simulations: The realism of the VR simulations used in these studies can also be a limiting factor. If the VR environment does not accurately reflect real-world driving conditions, the physiological responses observed may not accurately represent the stress responses of drivers in real-world situations.

- There is no standardized way to determine the appropriate complexity of driving scenarios, affecting stress levels and engagement.

Our work differs from previous studies by using more generalized scenarios, allowing our VR driving game to reach a wider audience. Additionally, our emphasis on statistical analysis provides deeper insights into our results, enhancing the overall understanding and applicability of our findings.

3. EXPERIMENT

The experiment was done at Kennesaw State University in an Experimental Studies Lab, that featured a Logitec Car Simulator, with a monitor hooked up to it. A total of 14 participants partook in the study (8 males: Mean = 22.89 years, STD = 2.67 years, 6 females: Mean = 21.20 years. STD = 1.30 years). All participants were 18 and over.

Participant Recruitment
Information about the study was disseminated via email, flyers, and the university's Reddit page. Interested students received a self-report questionnaire to gather basic information about their driving experience, health history, and general well-being, including their physical and mental health and experiences with driving and VR technology.

After completing the questionnaire, participants were emailed a consent form to fill out and return to the PIs. Session times for the study were then scheduled using the online tool Doodle. Each one-on-one study session lasted 45-55 minutes, with 3 to 5 minute breaks as needed.

Upon arrival, participants were asked about their current mental and physical health and familiarity with VR. They then received brief instructions on the game controls before beginning the game.

VR Driving Game
The VR Driving Game was developed by a team of four undergraduate students using the Unity 3D game engine during spring semester (January to April). The Researcher coordinated with the team through weekly meetings to ensure the game aligned with the study's objectives. The game featured low-poly textures for optimized performance and ran on a Windows 10 ASUS laptop with an NVIDIA 2060 GPU, Intel Core i5 processor, and 16 GB of RAM.

The VR Driving Game consisted of 3 levels, briefly explained below:

- Scenario 1: This takes place at a Grocery Store. Participants need to find and enter a parking space. As they reverse, a pedestrian or shopping cart unexpectedly appears behind the vehicle, requiring an abrupt stop to avoid a collision.

- Scenario 2: This also includes a scenario set in a grocery store. However, the participant must then leave the grocery store to navigate a moderate-traffic, daytime urban simulation. A key event during this simulation is a sudden stop by police for an alleged traffic violation.

- Scenario 3: Following a preset route, the key event is a sudden brake by the vehicle in front, causing a minor accident.

In the game, participants used Meta Quest 2 controllers for steering and menu navigation. A calming voice guided participants through the game, aiming to reduce stress.

At startup, participants navigated the main menu using Meta Quest 2 controllers, selecting levels by gently turning the steering wheel to the right, as see in Figure 1. Different sound effects and visuals represented each scenario.

As seen in Figures 2a, 2b and 2c, the participants were instructed to sit inside the car simulator to simulate the feeling of sitting in an actual vehicle.

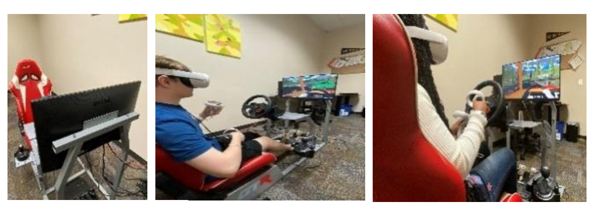

Figure 2a: Car Simulator Set up **2b: Male Participant** **2c: Female Participant**

After clearing each scenario, participants were asked if they wanted a 3 to 5 minute break. If they declined, they continued immediately. Upon

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completing all three scenarios, they were questioned about their feelings on the game and the guiding voice, and asked for improvement suggestions. Participants then received a $30 Amazon gift card and filled out a post-study questionnaire.

First Level
In the first level, set in a grocery store, players are guided to drive into a parking space, with a voice praising their turns and reminding them to stay aware of their surroundings. Blue circular waypoints indicate where players need to go. As they approach, they are warned about a family putting away groceries and instructed to back up to give a car space to exit. They are also cautioned about a nearby child chasing a ball, prompting extra caution. Next, players are directed to a shopping cart waypoint to have enough room to back into a parking spot. While attempting to park, they encounter a pedestrian, requiring careful maneuvering to avoid hitting them. Figures 3a, 3b, and 3c display pictures of this grocery level.

If players successfully navigate the level, the voice praises their caution. If they fail, hitting the family, child, or pedestrian, the voice gently reminds them that accidents happen and encourages them to take a deep breath and try again. Notably, only one participant hit the pedestrian behind their car while backing into the parking spot. When this happens, the pedestrian shouts, "Watch it!"

Second Level
In Scenario 2, players are instructed to back out of their parking space to leave the grocery store, with reminders to check their surroundings and mirrors. Blue waypoints guide them on where to drive. Upon approaching a turn, they are instructed to make a right turn. Shortly after, a police siren is heard, prompting the player to pull over. The police officer explains the reason for the stop and then allows the player to continue driving. Figure 4 shows a snapshot of the second level.

Figure 4: 2nd Level - Policeman.

Third Level
The third level and last level of the game takes place after the second level. In the third level of the game, the players are instructed to drive on the road. At some point in the game, the player is warned that a car in front of them is breaking hard. A blue waypoint appears in front of the player, close to the car in front of them so that they may brake in time, not hitting the car. Figure 5 demonstrates a snapshot of this.

Figure 5: Level 3 scenario.

If players crash into the car ahead, they fail the level and are respawned to try again. After successfully braking, the car in front drives away. Shortly after, another car hits the player from behind. Players are reminded to stay calm and drive to the nearest gas station. A blue waypoint guides them to a parking spot. Upon parking, the car that hit the player arrives, and the driver apologizes and takes responsibility. Figure 6 illustrates this interaction.

Figure 6: Driver in Green shirt.

4. INTIAL ANALYSIS: SELF REPORT QUESTIONAIRE RESULTS

Upon reviewing the self-report questionnaire, participants identified several driving difficulties, categorized into Situational Awareness, Specific Maneuvers, Multitasking and Cognitive Load, and Distance and Speed Management. The number of responses for each category out of 14 participants is detailed in Figure 7. As shown in the pie chart, "Specific Maneuvers" received the highest

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number of responses, indicating it as the most cited difficulty among participants. Additionally, participants rated their driving skills on a scale from poor to excellent. The majority rated their skills as "good," as depicted in Figure 8. Comparing genders, male participants more often rated their driving skills as "good" or "excellent," while female participants were more likely to rate themselves as "average."

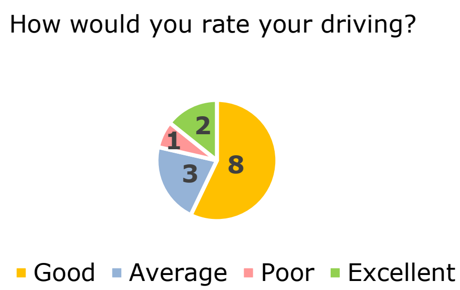

Figure 7: Driver Difficulty Category Responses.

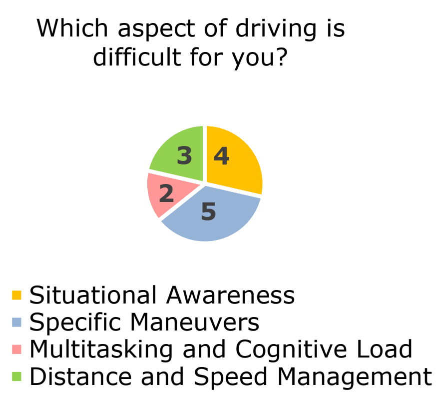

Figure 8: Driver Skill Ratings Distribution.

5. DATA COLLECTION AND PREPROCESSING

Data Collection

Physiological data was collected using the EmbracePlus Smartwatch while participants engaged with the VR game. The EmbracePlus, a medical-grade wearable, gathered various physiological parameters, which were transferred via Bluetooth to the Empatica CareLab app. The app analyzed the data, extracted digital biomarkers, and uploaded the information to the Empatica Cloud for secure storage and access via the Care Portal. This portal allowed team members to manage studies and visualize participants' biomarkers. Data was organized into a primary "participant_data" folder with subfolders for different dates.

Data Preprocessing

Preprocessing involved examining and modifying the data stored in a hierarchical directory structure. A Python script verified the directory, traversed subdirectories, and targeted 'digital_biomarkers' and 'aggregated_perminute.' It listed CSV files, loaded them into pandas DataFrames, converted timestamps to Eastern Time, and dropped 'missing_value_reason' columns. Cleaned data was saved back in a suitable format for analysis.

To address missing values, the script generated random values within specified ranges for EDA, pulse rate, and temperature, filling in missing data appropriately. Given the small dataset size, dropping rows was not a viable option as it would result in significant data loss and reduce the statistical power of the analysis. While regression-driven data imputation was considered, it was deemed less practical due to the limited data points and potential overfitting risks. Additionally, generating random values allowed for greater control over the imputation process, ensuring consistency and reliability in the data. This method ensured complete, properly formatted data covering the ideal time range for each participant.

Finally, the script identified all 'modified.csv' files, checked for remaining missing values, and confirmed data readiness for analysis by iterating over each DataFrame and reporting missing values. This quality assurance measure ensured comprehensive data for subsequent analysis.

6. DATA ANALYSIS AND RESULTS

Stationarity Testing and Initial Results

Our data analysis primarily focused on three variables: EDA, pulse rate, and temperature, using the modified CSV files. Initial exploration revealed minimal outliers. To ensure reliable time series analysis, we conducted the Augmented Dickey-Fuller (ADF) test to check for stationarity in our data. We found some non-stationary data, which required rectification.

To address this, we implemented a script with a loop that, for each metric (EDA, pulse rate, temperature), performed the ADF test, checked if differencing was required, and applied the appropriate order of differencing. If a series remained non-stationary after first-order differencing, the script applied second-order differencing and rechecked for stationarity. This process continued until all series were stationary,

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ensuring our data was primed for accurate and meaningful analysis. First-order differencing reveals the rate of change between consecutive observations, making it easier to analyze seasonality and cyclical patterns. Second-order differencing is useful for addressing quadratic trends by removing the trend in the rate of change, highlighting any underlying seasonality or long-term cycles.

In our case, many series were initially non-stationary. EDA and pulse rate series became stationary after applying first-order differencing. Several temperature series required second-order differencing to become stationary.

After achieving stationarity, we analyzed how EDA, pulse rate, and temperature changed over time for all participants.

RQ1: Were the participants less or more stressed as they played the VR Driving Game?

Figures 9, 10, and 11 show a general trend (trend line shown in red) of reduced stress levels among participants playing the VR Driving Game. The methods used for the trendlines in Figures 9, 10, and 11 were LOESS (Locally Weighted Scatterplot Smoothing) for EDA with the frac parameter set to 0.20, Polynomial Regression for Pulse Rate with the degree set to 5, and Moving Average for Temperature with the window size being set to 10. LOESS is a non-parametric method that can flexibly fit curves to data by performing multiple localized regressions. This is particularly useful when the data exhibits non-linear patterns that a simple linear model cannot capture. Furthermore, by fitting a polynomial of a specified degree to the data, Polynomial Regression can model non-linear relationships. This allows the trend line to bend and fit the data more accurately than a straight line, capturing the underlying patterns more effectively. Given the non-linearity of the physiological responses, using regular linear regression modelling would have oversimplified these responses, leading to inaccurate trend readings.

Regarding RQ1, our analysis revealed that 12 out of 14 participants experienced a decrease in EDA, indicating reduced stress or arousal and suggesting increased relaxation over time. Similarly, pulse rates decreased in 10 out of 14 participants, further supporting the notion of relaxation. Additionally, 8 out of 14 participants showed a decrease in temperature, indicating physical cooling down as they played.

Further analysis of gender-specific trends revealed some differences. Two out of six female participants experienced a temperature decrease, and only one had an increased pulse rate. In contrast, among male participants, only one showed an increase in EDA, while three had increased pulse rates, and six experienced a decrease in temperature. These variations suggest that gender may influence physiological responses to stress, but overall, stress reduction was observed across both male and female participants.

Therefore, the answer RQ1 is that most participants, regardless of gender, experienced reduced stress, suggesting that the VR Driving Game had a generally calming effect over time.

RQ2: Which physiological metric was the most significant for the participants, and which were the most consistently statistically significant overall?

To answer RQ2, we calculated Cohen's D results for the three metrics (EDA, pulse rate, and temperature) for each participant, as shown in Table 1. Cohen's D measures effect size, interpreted as follows:

- Small effect size: d ≈ 0.2
- Medium effect size: d ≈ 0.5
- Large effect size: d ≈ 0.8

As such, we can generalize the following findings:

- Pulse Rate vs. Temperature: Pulse rate generally shows a positive relationship with temperature across participants, meaning that higher temperatures tend to correlate with higher pulse rates. This aligns with the physiological response where increased body temperature can lead to higher heart rates as the body works to regulate its internal temperature.

- Pulse rate generally shows higher values compared to temperature across participants, consistent with the expected physiological response where pulse rate increases in response to various stimuli or activities, whereas body temperature fluctuates within a narrower range under normal conditions.

- EDA vs. Pulse Rate: Across most participants, EDA tends to show either lower or higher activity compared to pulse rate. This suggests that in some individuals, changes in electrodermal activity might correlate positively with

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changes in pulse rate, indicating a potential physiological response pattern.

Next, we assessed the statistical significance of our results to ensure practical meaning behind our findings, as shown in Table 2. Statistically significant results were found for the following participants in terms of EDA, Pulse Rate and Temperature:

- EDA: Participants 1,2, 11, 12, 13
- Pulse Rate: Participants 7, 9, 10, 11, 13, 14
- Temperature: Participants 1, 5, 7, 10, 2, 11, 12, 13.

Significant changes in EDA were observed for five participants, while significant changes in pulse rate were noted for six participants, suggesting substantial changes in heart rate potentially related to stress. Significant changes in temperature were observed for eight participants.

To further validate our findings, we used bootstrapping for Cohen's D. Bootstrapping, a resampling technique, estimates statistics on a population by sampling a dataset with replacement. It is particularly useful when data normality is in doubt, or the sample size is small. In our case, the dataset is small, necessitating extra caution in interpreting findings. Bootstrapping can be particularly useful for the following reasons:

- Confidence Intervals: Bootstrapping can be used to construct confidence intervals around the Cohen’s D statistic. This provides a range of plausible values for the population parameter and gives an indication of how precise the estimates are.

- Small Sample Sizes: Cohen’s D is sensitive to the assumption of normality. When the sample size is small, this assumption may not hold, and the estimate of Cohen’s D may be biased. Bootstrapping does not rely on the assumption of normality and can provide a more accurate estimate in these cases.

- Stability of the Estimate: By resampling the data multiple times and calculating Cohen’s D for each sample, we can get a sense of the variability or stability of our estimate. If the bootstrapped estimates of Cohen’s D vary widely, it suggests that the original estimate may not be reliable.

Significance across all participants was determined by examining the confidence intervals (CI Low and CI High) of Cohen's D values for each metric. A metric is considered significant if its confidence interval does not include zero, indicating a reliable effect size.

Based on this analysis, as shown in Table 3, temperature emerged as the most consistently significant metric, with significant results in nine participants. EDA was significant for six participants, and pulse rate for five participants. As such, we can conclude that for RQ2, temperature is likely the most reliable indicator of physiological changes, showing consistent significance across participants.

RQ3: Were there any significant findings in terms of gender?

The analysis next focused on potential gender-based differences, as detailed in Table 4. We found that pulse rate increases were more pronounced in male participants compared to females. Female participants showed mixed results, with some displaying positive effect sizes and others negative. Overall, significant differences between male and female participants were observed.

Notably, as shown in Tables 5 through 7, gender had a significant effect on both EDA (P>|z| = 0.000) and temperature (P>|z| = 0.001). These results indicate meaningful physiological differences between males and females for these metrics.

To further refine our understanding, we employed Quantile Regression in addition to traditional mixed models. Unlike standard models, which assume normally distributed residuals, quantile regression does not require this assumption. This makes it better suited to handling non-normal data and outliers, allowing for a more nuanced exploration of the relationships between gender and physiological metrics such as EDA, pulse rate, and temperature. By estimating the conditional median or other quantiles, quantile regression provided insights that traditional models might have missed, especially in skewed distributions.

Specifically, we were interested in how the relationships between gender and outcomes (e.g., EDA, pulse rate, and temperature) varied across different parts of the distribution. While mixed models offered insight into the average effects of gender, quantile regression revealed how gender influenced different segments of the outcome distribution. This combined approach allowed us to capture both overall trends and the

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specific ways gender affected physiological responses, offering a more comprehensive understanding of its impact on EDA, pulse rate, and temperature.

The results of the quantile regression analysis showed that gender had a particularly significant effect on EDA for female participants, as demonstrated in Table 8. This suggests that the physiological response to the VR Driving Game, particularly in terms of EDA, differed notably by gender, with female participants exhibiting distinct patterns compared to their male counterparts. Thus, we can conclude that for RQ3, there were significant findings in terms of gender.

RQ4: Did the VR Driving Game have a positive impact on the participants?
After playing the game, participants completed a post-study questionnaire. This questionnaire included questions about which level they found most stressful and whether the guiding voice was helpful in calming them down and providing instructions.

As shown in Figure 12, Scenario 1 was the most stressful for both male and female participants. Interestingly, Scenario 3 was the second most stressful among female participants, while none of the female participants found Scenario 2 to be stressful.

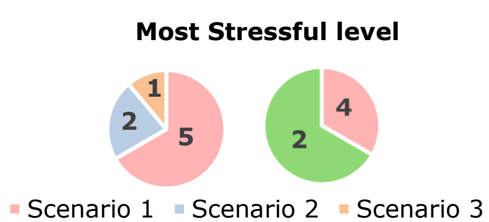

Figure 12: Stressful Scenario Responses – Male (left) and Female (right)

When evaluating the effectiveness of the calming voice in terms of helpful hints, intervention, and overall appreciation, none of the participants found the voice annoying, and most found the voice's interventions effective and helpful. Additionally, none of the participants were dissatisfied with the game or the voice, finding it helpful and calm.

Figure 13 represents the participants' responses regarding their satisfaction with the VR game. Interestingly, three male participants rated the effectiveness of the voice's interventions as neutral. Similar findings were observed when evaluating whether the voice was helpful and when asked about the instructions and guidance provided by the voice. Overall, we can conclude that for RQ4, the VR driving game had a positive impact on the participants.

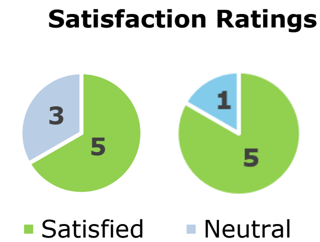

Figure 13: VR Game Satisfaction ratings – Male (left) and Female (right)

7. CONCLUSIONS

This project provided a detailed examination of biometric data from participants engaged in a driving simulation. By utilizing various statistical methods, significant insights were gained regarding the differences in biometric responses based on gender and other factors.

Our findings and analysis revealed that the effect of gender on biometric responses was significant. Our analysis revealed that female participants exhibited notable changes in EDA and temperature, suggesting a notable physiological response to the driving simulation (Kerautret et al., 2021). This aligns with broader research findings indicating that women often show stronger physiological responses to stress in driving scenarios compared to men (Mostowfi & Kim, 2022).

Studies revealed that women often have faster, larger, and longer-lasting stress responses compared to men. For example, women have more receptors for stress-related neurotransmitters, and their stress responses, such as increased heart rate and electrodermal activity, can be more pronounced and prolonged (James et al., 2023; Wang et al., 2007). Studies also have observed that women often report higher levels of stress and anxiety in driving situations compared to men, leading to more significant physiological reactions such as increased heart rates and electrodermal activity (Arca, 2022; Antoun, 2017).

In our case, temperature and EDA have shown to be more reliable metrics for measuring driving stress compared to pulse rate. EDA directly measures sympathetic nervous system activity, providing real-time data on psychological or physiological arousal, while temperature changes reflect peripheral responses to stress.

While our study's sample size was limited, the observed trends are consistent with broader research findings on gender differences in physiological responses to driving stress.

8. FUTURE WORKS

Even though our VR driving game was successful, we plan to expand it based on participants' valuable suggestions. Participants recommended incorporating additional scenarios to increase realism and stress responses, such as inclement weather conditions like driving in the rain or nighttime driving. One participant suggested that the policeman in the simulation should be more aggressive, while two others recommended adding distractions such as music or phone calls to further simulate real-world driving. Enhancing the environment by adding more people or livelier scenery was another suggestion, as well as incorporating more interactive features with the Meta Quest 2 controllers, such as honking the horn or using turn signals.

In future iterations, we aim to add even more varied stress-inducing scenarios, such as receiving sudden instructions from a co-pilot, being cut off by another driver, engaging in a heated argument with passengers, or missing an exit due to a vehicle blocking the passing lane. These scenarios would provide opportunities to explore individual differences in responses to a wider range of stressful driving situations. For example, while some drivers might remain calm, others could experience heightened stress or road rage, giving us valuable insights into how personality traits influence stress responses.

Another area for improvement involves standardizing the breaks between game sessions. Consistent break durations will help control for reductions in adrenaline levels and ensure comparability across scenarios. Future studies will implement uniform breaks to maintain consistency in the physiological data collected.

We also recognize that the calming voice used in this study may have influenced participants' stress levels by reducing the emotional impact of stressful scenarios. Future studies could investigate how different voice tones—such as critical or chiding voices—affect participants' stress responses. Additionally, introducing scenarios where an accident is inevitable, without prior warning, could provide insight into how drivers react when failure is unavoidable.

Regarding data collection, expanding beyond the current reliance on wearables could yield richer insights. In future studies, we plan to collect additional data, such as facial expressions, eye movements, or galvanic skin response, to better understand the full range of participants' stress responses during driving simulations. If funding allows, these enhancements will help provide a more comprehensive view of stress dynamics.

9. ACKNOWLEDGEMENTS

We extend our gratitude to our undergraduate team for developing the game. The Principal Investigator (PI) supervised the game's quality, with refinements made by the PI's advisor. This project was sponsored by the Foundation for Neurofeedback and Neuromodulation Research (FNNR) through Mini-Grant #501-2023.

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APPENDIX A – Figures

Figure 1: Main Menu of the game. The three floating rocks represent the levels of the game.

Figure 3a: Grocery Parking lot with Blue waypoint.

Figure 3b: Child with ball (circled in red).

Figure 3c: Backing into Pedestrian (circled in blue).

Figure 3: Grocery Level

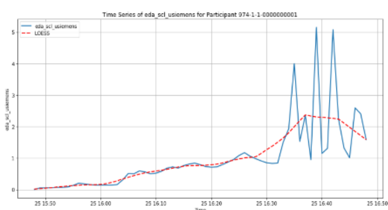

Figure 9a: Participant 1(M)

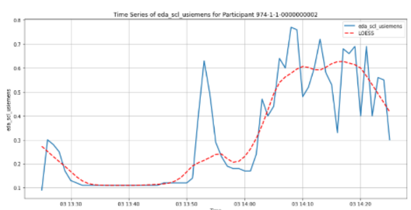

Figure 9b: Participant 2(M)

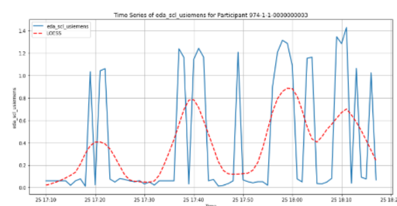

Figure 9c: Participant 3(M)

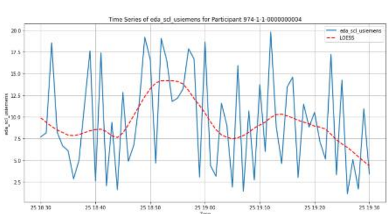

Figure 9d: Participant 4(F)

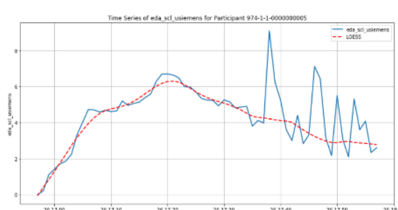

Figure 9e: Participant 5(F)

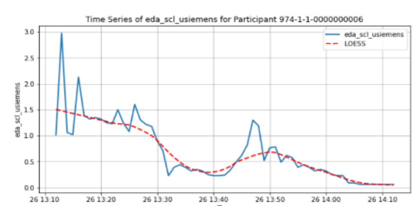

Figure 9f: Participant 6(F)

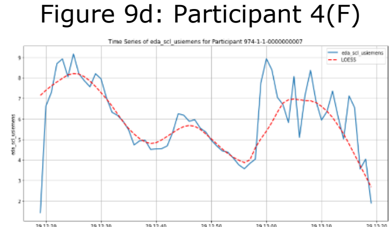

Figure 9g: Participant 7(M)

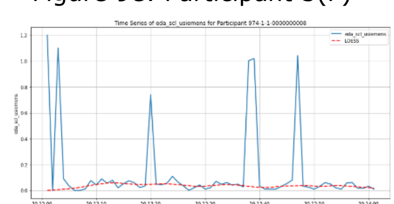

Figure 9h: Participant 8(F)

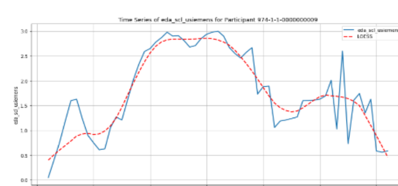

Figure 9i: Participant 9(M)

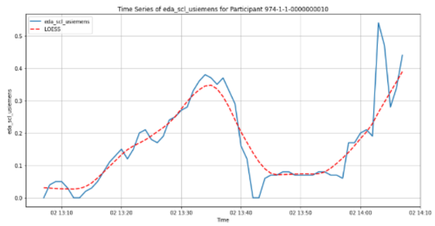
Figure 9j: Participant 10(M)

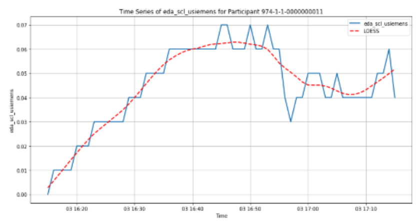
Figure 9k: Participant 11(F)

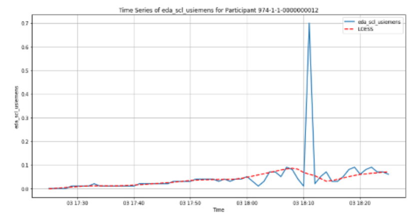
Figure 9l: Participant 12(M)

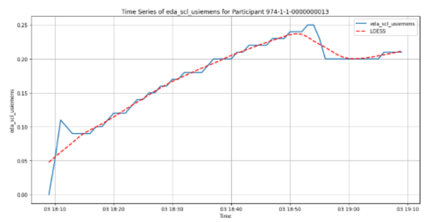
Figure 9m: Participant 13(F)

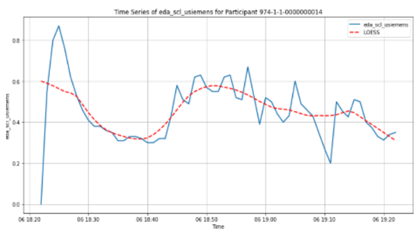
Figure 9n: Participant 14(M)

Figure 9: Participant's EDAs over time.

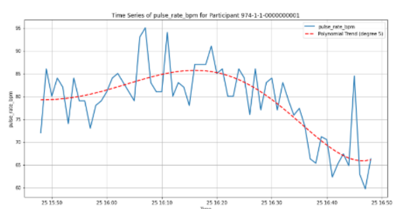
Figure 10a: Participant 1 (M)

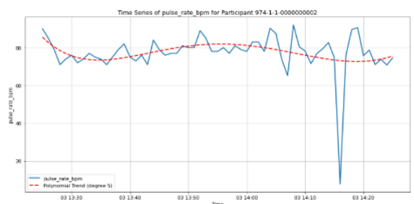
Figure 10b: Participant 2 (M)

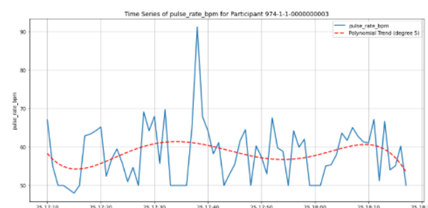
Figure 10c: Participant 3 (M)

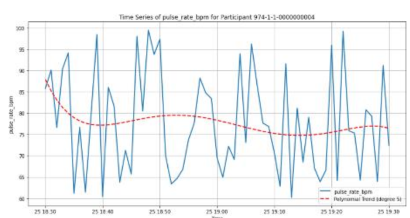
Figure 10 d: Participant 4 (F)

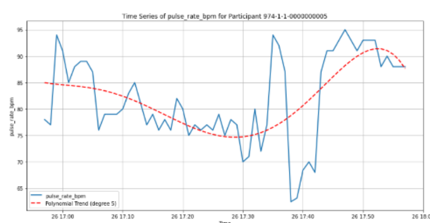
Figure 10e: Participant 5 (F)

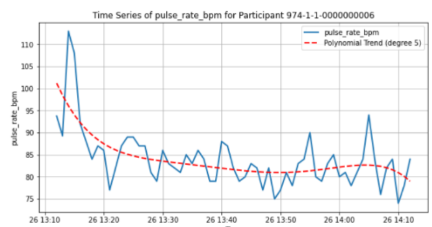
Figure 10f: Participant 6 (F)

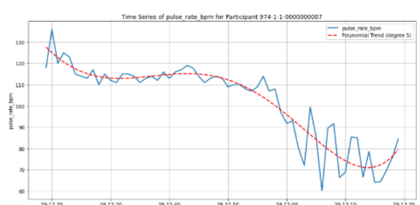
Figure 10g: Participant 7 (M)

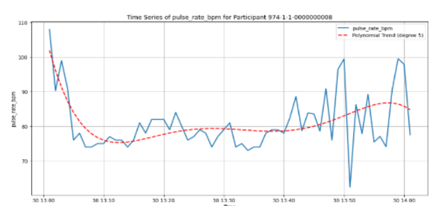
Figure 10h: Participant 8 (F)

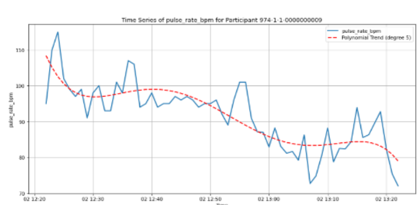
Figure 10i: Participant 9 (M)

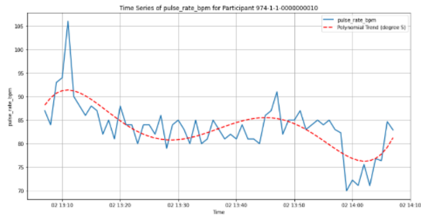
Figure 10j: Participant 10 (M)

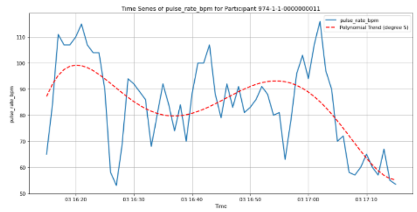
Figure 10k: Participant 11 (F)

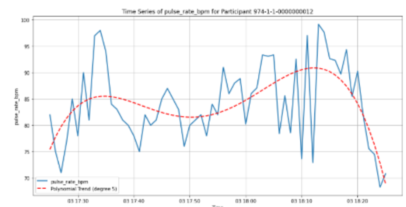
Figure 10l: Participant 12 (M)

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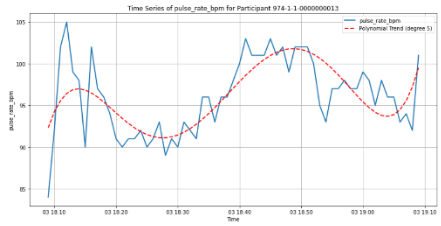

Figure 10m: Participant 13 (F)

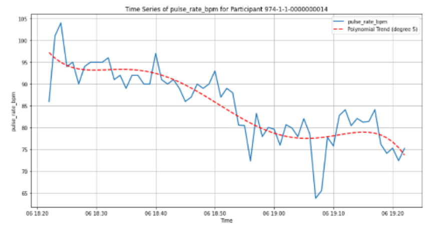

Figure 10n: Participant 14 (M)

Figure 10: Participants' Pulse Rates Over time.

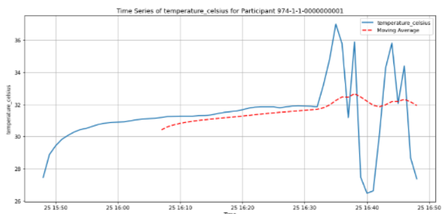

Figure 11a: Participant 1(M)

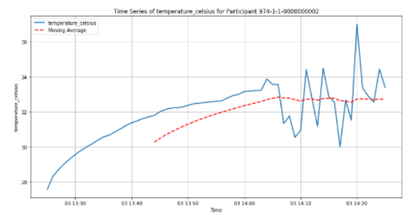

Figure 11b: Participant 2 (M)

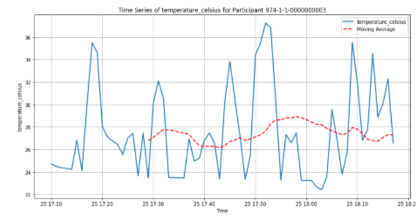

Figure 11c: Participant 3 (M)

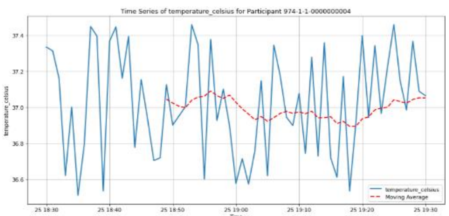

Figure 11d: Participant 4 (F)

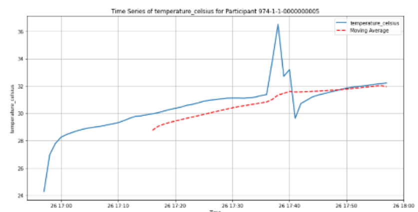

Figure 11e: Participant 5 (F)

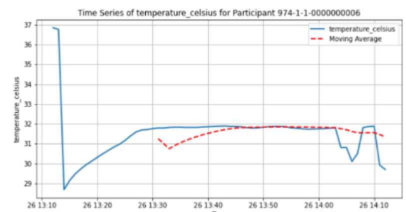

Figure 11f: Participant 6 (F)

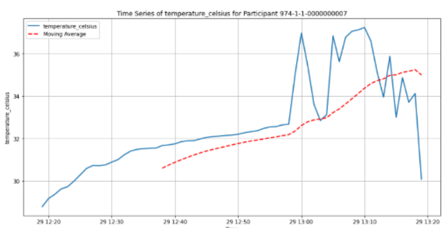

Figure 11g: Participant 7 (M)

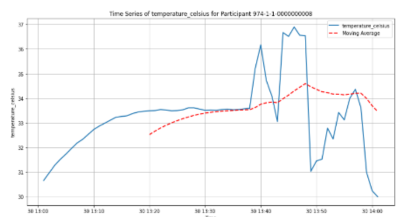

Figure 11h: Participant 8 (F)

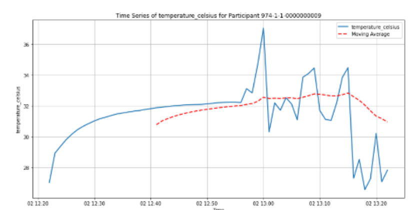

Figure 11i: Participant 9 (M)

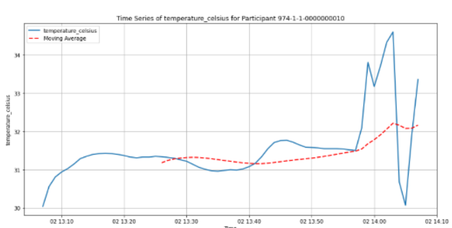

Figure 11j: Participant 10 (M)

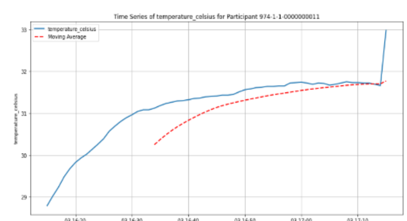

Figure 11k: Participant 11 (F)

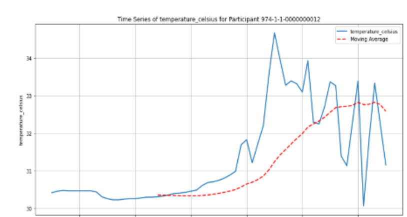

Figure 11l: Participant 12 (M)

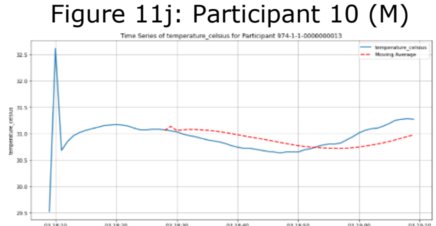

Figure 11m: Participant 13 (F)

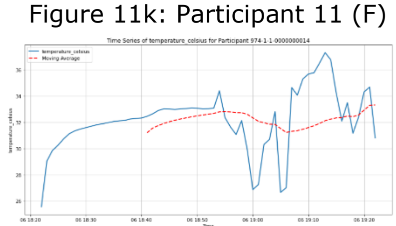

Figure 11n: Participant 14 (M)

Figure 11: Participants' Temperatures Over time.

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APPENDIX B – Tables

Table 1. Participant Metrics with Cohen's D

Participant	Metric	Cohen's D
1	EDA	-1.438387
	Pulse Rate	0.838545
	Temperature	-0.587648
2	EDA	-0.344259
	Pulse Rate	-0.233768
	Temperature	-0.294475
3	EDA	0.336248
	Pulse Rate	0.298969
	Temperature	0.181656
4	EDA	-0.039809
	Pulse Rate	-0.227438
	Temperature	-1.901704
5	EDA	0.335254
	Pulse Rate	2.067079
	Temperature	-2.005618
6	EDA	0.033700
	Pulse Rate	-0.170715
	Temperature	-0.546009
7	EDA	0.188297
	Pulse Rate	1.972688
	Temperature	-0.214628
8	EDA	-0.079148
	Pulse Rate	0.791275
	Temperature	-0.918734
9	EDA	-1.774026
	Pulse Rate	0.103837
	Temperature	-1.393755
10	EDA	-0.796594
	Pulse Rate	0.610066
	Temperature	-1.870847
11	EDA	-0.649005
	Pulse Rate	-0.456534
	Temperature	-2.319676
12	EDA	-2.398581
	Pulse Rate	-1.229099
	Temperature	0.420771
13	EDA	0.030003
	Pulse Rate	2.768771
	Temperature	-0.314131
14	EDA	0.030003
	Pulse Rate	2.768771
	Temperature	-0.314131

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Table 2: Statistical Analysis Results for Participants

Participant	Metric	Statistic	p-value	Adjusted p-value
1	EDA	16	9.68e-11	9.21e-10
	Pulse Rate	631	1.68e-02	3.28e-02
	Temperature	184	5.16e-05	1.34e-04
2	EDA	74	1.41e-08	5.51e-08
	Pulse Rate	424	5.58e-01	6.16e-01
	Temperature	116	4.96e-07	1.61e-06
3	EDA	494	3.04e-01	3.95e-01
	Pulse Rate	541.5	6.57e-01	6.92e-01
	Temperature	459	1.46e-01	2.27e-01
4	EDA	555	1.96e-01	2.84e-01
	Pulse Rate	539	2.88-01	3.88e-01
	Temperature	516	4.66e-01	5.51e-01
5	EDA	505	5.68e-01	6.16e-01
	Pulse Rate	386	2.56e-01	3.57e-01
	Temperature	18	1.18e-10	9.21e-10
6	EDA	298.4	1.96e−01	3.95e−01
	Pulse Rate	504.5	1.28e−02	3.18e−02
	Temperature	258.7	5.16e−05	5.51e−06
7	EDA	560	1.72e-01	2.59e-01
	Pulse Rate	908.5	1.57e-10	1.02e-09
	Temperature	24	2.08e-10	1.16e-09
8	EDA	533	3.29e-01	4.15e-01
	Pulse Rate	416.5	4.87e-01	5.59e-01
	Temperature	290	1.18e-02	2.55e-02
9	EDA	520	4.31e-01	5.26e-01
	Pulse Rate	862.5	9.92e-09	4.30e-08
	Temperature	316	3.21e-02	5.70e-02
10	EDA	445.5	7.83e-01	7.83e-01
	Pulse Rate	642	1.05e-02	2.54e-02
	Temperature	171.5	2.35e-05	6.57e-05
11	EDA	295	1.24e-02	2.55e-02
	Pulse Rate	626.5	2.01e-02	3.73e-02
	Temperature	0	2.01e-11	6.55e-10
12	EDA	96.5	8.23e-08	2.91e-07
	Pulse Rate	329.5	5.13e-02	8.70e-02
	Temperature	30	3.59e-10	1.75e-09
13	EDA	12	4.84e-11	6.55e-10
	Pulse Rate	172	2.30e-05	6.57e-05
	Temperature	641.5	1.10e-02	2.54e-02
14	EDA	444.5	7.72e-01	7.83e-01
	Pulse Rate	920.5	5.04e-11	6.55e-10
	Temperature	356	1.17e-01	1.90e-01

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Table 3: Cohen's D Effect Size with 95% Confidence Intervals for EDA, Pulse Rate, and Temperature Bootstrap results

Participant	Metric	Cohen's D	CI Low	CI High
1	EDA	-1.552439	-2.10668	-1.25101
	Pulse Rate	0.870001	0.398781	1.367424
	Temperature	-0.643849	-1.26489	-0.10594
2	EDA	-0.345983	-0.86209	0.146409
	Pulse Rate	-0.171072	-0.49966	0.423803
	Temperature	-0.399335	-0.84821	-0.11594
3	EDA	0.347545	-0.1795	0.932074
	Pulse Rate	0.316637	-0.20479	0.853623
	Temperature	0.209698	-0.32162	0.737244
4	EDA	-0.02913	-0.52006	0.511049
	Pulse Rate	-0.251052	-0.86183	0.283087
	Temperature	-2.046014	-2.79041	-1.6159
5	EDA	0.333029	-0.20766	0.893306
	Pulse Rate	2.163959	1.705	2.756521
	Temperature	-2.102134	-2.6564	-1.62448
6	EDA	0.023903	-0.49015	0.534756
	Pulse Rate	-0.197559	-0.78951	0.302591
	Temperature	-0.589378	-1.18137	-0.1286
7	EDA	0.201216	-0.3232	0.752456
	Pulse Rate	2.073197	1.505642	2.764266
	Temperature	-0.249412	-0.829	0.300268
8	EDA	-0.077495	-0.5819	0.489859
	Pulse Rate	0.822014	0.405876	1.220347
	Temperature	-0.957564	-1.29143	-0.57238
9	EDA	-1.885303	-2.72735	-1.20656
	Pulse Rate	0.038468	-0.60327	0.463783
	Temperature	-1.457263	-1.95483	-0.98055
10	EDA	-0.83616	-1.38334	-0.35839
	Pulse Rate	0.63936	0.097418	1.2171
	Temperature	-1.937372	-2.36652	-1.59867
11	EDA	-1.100321	-2.3537	-0.56637
	Pulse Rate	-0.503784	-1.13235	0.016751
	Temperature	-2.443558	-3.18736	-1.8778
12	EDA	-2.511189	-3.2005	-1.97447
	Pulse Rate	-1.313049	-2.02982	-0.69726
	Temperature	0.468322	-0.01906	1.078587
13	EDA	0.035349	-0.46564	0.511139
	Pulse Rate	2.911906	2.362222	3.64434
	Temperature	-0.326803	-0.90044	0.210485
14	EDA	0.035349	-0.46564	0.511139
	Pulse Rate	2.911906	2.362222	3.64434
	Temperature	-0.326803	-0.90044	0.210485

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Table 4: Cohen's D Results for Male and Female Participants

Participant	Gender	Metric	Cohen's D	CI Low	CI High
1	Male	EDA	-1.547	-2.057	-1.246
		Pulse Rate	0.866	0.381	1.372
		Temperature	-0.634	-1.223	-0.109
3	Male	EDA	-0.359	-0.863	0.14
		Pulse Rate	-0.169	-0.462	0.429
		Temperature	-0.39	-0.835	-0.119
7	Male	EDA	0.35	-0.157	0.87
		Pulse Rate	2.169	1.682	2.779
		Temperature	-2.094	-2.68	-1.614
9	Male	EDA	0.198	-0.304	0.78
		Pulse Rate	2.066	1.532	2.725
		Temperature	-0.235	-0.797	0.267
_10	Male	EDA	-0.09	-0.57	0.432
		Pulse Rate	0.811	0.388	1.225
		Temperature	-0.956	-1.303	-0.568
2	Male	EDA	-1.855	-2.596	-1.219
		Pulse Rate	0.044	-0.618	0.466
		Temperature	-1.45	-1.961	-1.009
12	Male	EDA	-1.096	-2.331	-0.565
		Pulse Rate	-0.502	-1.112	-0.002
		Temperature	-2.466	-3.254	-1.885
14	Male	EDA	0.027	-0.528	0.531
		Pulse Rate	2.936	2.348	3.676
		Temperature	-0.341	-0.91	0.186
4	Female	EDA	0.367	-0.162	0.932
		Pulse Rate	0.328	-0.211	0.86
		Temperature	0.189	-0.333	0.741
5	Female	EDA	-0.033	-0.519	0.53
		Pulse Rate	-0.248	-0.847	0.297
		Temperature	-2.031	-2.645	-1.62
6	Female	EDA	1.396	0.250	3.043
		Pulse Rate	-2.610	-2.75	-2.47
		Temperature	0.382	0.140	0.423
8	Female	EDA	0.034	-0.492	0.563
		Pulse Rate	-0.182	-0.759	0.324
		Temperature	-0.57	-1.104	-0.056
11	Female	EDA	-0.808	-1.348	-0.327
		Pulse Rate	0.632	0.071	1.232
		Temperature	-1.937	-2.346	-1.614
13	Female	EDA	-0.808	-1.348	-0.327
		Pulse Rate	0.632	0.071	1.232
		Temperature	-1.937	-2.346	-1.614

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Table 5: Mixed Linear Model Results for Temperature

Mixed Linear Model Regression Results: Temperature						
Model: MixedLM Dependent Variable: temperature_celsius						
No. Observations: 7228 Method: REML						
No. Groups: 14	Scale:	84.7764				
Min. group size: 61	Log-Likelihood:	-26306.7				
Max. group size: 6428	Converged:	Yes				
Mean group size: 516.3						
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	31.798	0.374	85.049	0	31.065	32.531
Gender[T.girl]	0.748	0.221	3.383	0.001	0.315	1.182
Group Var	0.713	0.099				

Table 6: Mixed Linear Model Results for Pulse Rate

Mixed Linear Model Regression Results: Pulse Rate						
Model: MixedLM Dependent Variable: pulse_rate_bpm						
No. Observations: 7228 Method: REML						
No. Groups: 14	Scale:	472.8996				
Min. group size: 61	Log-Likelihood:	-32529.4233				
Max. group size: 6428	Converged:	Yes				
Mean group size: 516.3						
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	83.589	2.310	36.185	0.000	79.061	88.116
Gender[T.girl]	0.646	0.539	1.198	0.231	-0.411	1.703
Group Var	66.988	1.346				

Table 7: Mixed Linear Model Results for EDA

Mixed Linear Model Regression Results: EDA						
Model: MixedLM Dependent Variable: eda_scl_usiemens						
No. Observations: 7228 Method: REML						
No. Groups: 14	Scale:	11.2280				
Min. group size: 61	Log-Likelihood:	-19024.4145				
Max. group size: 6428	Converged:	Yes				
Mean group size: 516.3						
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	1.244	0.727	1.712	0.087	-0.180	2.668
Gender[T.girl]	1.634	0.083	19.576	0.000	1.470	1.798
Group Var	7.209	0.869				

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Table 8: Quantile Regression Results for EDA

Results for eda_scl_usiemens (Quantile Regression)						
Dependent Variable: eda_scl_usiemens						
Model: QuantReg						
Method: Least Squares						
Date: Saturday, 13 July 2024	Psuedo R-Squared	0.005317				
Time: 05:11:55	Bandwidth:	0.7388				
	Sparcity:	1.681				
	No. Observations:	800				
	Df Residuals:	798				
	Df Model:	1				
	Coef.	Std. Err.	t	P>|t|	[0.025	0.975]
Intercept	0.4000	0.038	10.591	0.000	0.326	0.474
Gender[T.girl]	-0.2000	0.061	-3.270	0.001	-0.320	-0.080

