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The Role of Stress Awareness in Mindless Overeating: HRV and EDA Study

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Abstract. Mindless eating, where individuals consume food without paying attention to hunger or satiety cues, is a significant contributor to overeating and associated health issues such as obesity and diabetes. This paper investigates the relationship between mindless eating and stress levels, hypothesizing that a lack of awareness of over-consumption during mindless eating reduces stress compared to mindful eating. In this work, we measured and compared changes in heart rate variability (HRV) and skin conductance (SC) during episodes of mindless and mindful overeating using Photoplethysmography (PPG) and Electrodermal Activity (EDA) sensors. Results indicated a significantly higher HRV during mindless eating ($p < 0.05$), suggesting that individuals experience less psychological stress during these episodes. This finding supports the hypothesis that reduced awareness of mindless eating is associated with lower stress levels, potentially contributing to continued overeating behaviour. The implications of this research underscore the need for further exploration into how awareness and mindfulness can influence eating habits and overall health.

Keywords: mindless eating, overeating, machine learning, wearable device, mHealth

1. Introduction

Mindless eating, which refers to the act of consuming food without paying attention to hunger or fullness cues, often happens during distracting activities such as watching television, working, or socializing. This type of eating can lead to excessive food intake, disrupting natural hunger regulation and energy balance mechanisms [1,2]. The increasing prevalence of mindless eating correlates with rising obesity rates and associated health issues, including cardiovascular disease, hypertension, and type 2 diabetes [3]. Addressing behaviours that contribute to excessive caloric intake and impaired energy balance is, therefore, crucial [1-3].

Previous research has explored various dimensions of overeating and obesity. Studies have shown that environmental cues—such as the availability and variety of foods as well as the portion sizes—significantly influence eating behavior [4]. For example, larger portions often lead to increased consumption regardless of hunger levels [5]. Using self-report questionnaires and behavioural

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assessments, emotional eating research has elucidated how emotions impact eating habits [6]. However, these studies frequently overlook the physiological responses associated with mindless eating. Sensory-normative models emphasize that external cues, including portion sizes and food variety, influence food intake [2]. This suggests that portion sizes can be considered a specific type of external cue or environmental factor influencing eating behaviour.

Current literature primarily focuses on behavioural and dietary modifications but lacks an in-depth examination of the physiological mechanisms behind mindless eating. Studies investigating stress and over-consumption, using stress induction and cortisol measurements, provide insights into stress-related eating behaviours [7,8]. However, gaps remain in understanding physiological responses such as heart rate variability (HRV) and skin conductance (SC) during mindless versus mindful eating [9,10].

This study aims to bridge this gap by investigating the physiological responses associated with mindless versus mindful eating, specifically examining HRV and SC as indicators of stress and awareness. By employing photoplethysmography (PPG) and Electrodermal Activity (EDA) sensors to measure these markers, the study seeks to clarify how mindless eating affects physiological stress and awareness. The study also seeks to find which sensors best detect stress changes between mindless and mindful eating states. This study hypothesizes that mindless eating will produce distinct physiological responses compared to mindful eating, as indicated by changes in HRV and SC. This research will enhance our understanding of how mindless eating contributes to overeating and other related health risks and will assist in developing more effective interventions for managing eating behaviours.

2. Methodology

2.1. Participants

A total of 26 participants were recruited for this study, comprised of 13 normal-weighted males (BMI between 18.5 and 24.9) and 13 normal-weighted females. Each participant underwent two experiments: mindless overeating while watching TV shows and mindful overeating without any distractions. Participants were allowed to choose their favourite snacks to consume and their favourite TV shows prior to the experiments.

2.2. Experimental setup

Each subject was equipped with a wearable microcontroller attached to an expansion board. EDA and PPG sensors were attached to the expansion boards to measure the physiological responses. These include skin conductance from the EDA sensor and heart rate from the PPG sensor. These factors will be measured during three distinct phases: before, during, and after mindless or mindful overeating. The device was worn on the participant's dominant hand. Before the experiments began, participants were instructed to refrain from eating, drinking coloured beverages, or engaging in intense exercise for two hours or more.

A separate room was designated for the experiment to minimize environmental influences on the participants' physiological measurements. The entire experiment was recorded with a camera set up in the room. Upon arrival, participants who had yet to eat or exercise vigorously were escorted into the designated room. The wearable device was placed on the participant's dominant hand after they entered the room, and a 5-minute acclimatization period allowed them to familiarize themselves with the environment and device in case their anxiety and heart rate stabilised.

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Participants were then required to begin the mindless eating experiment. During the mindless eating phase, they were allowed to consume their favourite snacks while watching their chosen TV show. During the mindful eating phase, they were asked to eat without distractions, focusing only on their food intake. In these experimental phases, they were informed that they could stop the experiment at any time. After the eating session, participants were asked to fill out the Mindless overeating scale questionnaire (see Figure 1). In the mindful eating experiment, participants were asked to eat without distractions, focusing solely on their food intake [11].

Dimension	Scale	#	Mindless Overeating Scale	Response type
Mindless Dimension	Attention level	1	The video appeals to me.	
		2	Most of my attention is on the video.	
	Feelings of fullness	3	I eat without being fully aware that I'm eating.	
		4	I don't feel full or uncomfortable when eating.	
	Awareness of eating movements	5	I eat automatically without realizing I'm doing it.	
		6	I don't pay attention to the act of eating.	
	Intention to stop	7	I have no subjective desire to stop eating.	
Overeating Dimension	Overeating level	8	I feel full.	
		9	I eat until I feel uncomfortably full.	
	Intention of food eaten	10	Before I start eating, I don't have an intention of how much to eat.	
		11	I eat more food than I intended to.	
	The psychological sensation of mindless overeating	12	I wanted to keep eating after being asked to stop.	
		13	I didn't feel stress when/after eating.	
		14	I didn't feel guilty when/after eating.	

Reporting Value	Mindless Overeating Scale
0	Not at all
1	Slightly
2	Moderate
3	Very much
4	Extremely

Figure 1. Mindless overeating scale

After each phase, the amount of food consumed was recorded and analyzed to calculate the total caloric intake. The data collected from the EDA and PPG sensors assessed the physiological responses during the eating sessions.

2.3. Data collection

A compact wearable system was developed to monitor physiological signals in ambulatory settings. The core component was the Seeed Studio XIAO nRF52840 (Sense) board, complemented by an Expansion Board Base. This expansion board integrated modules for battery charging, an OLED display, and an SD card slot for data storage. It also provided Grove connectors, enabling interfacing with analog sensors and serial communication peripherals (see Figure 2).

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Two key sensors were integrated - a PulseSensor PPG fingertip sensor for photoplethysmography and a Grove-compatible EDA analog sensor for measuring galvanic skin response. These were connected to the main board via the expansion board's interfaces. A rechargeable lithium-ion battery pack was also integrated to allow untethered mobile use.

The system utilized customized firmware based on the Arduino framework. It recorded PPG and EDA data for the first 3 minutes before overeating, during, and after overeating and then saved the multi-sensor data to an onboard SD card for subsequent analysis.

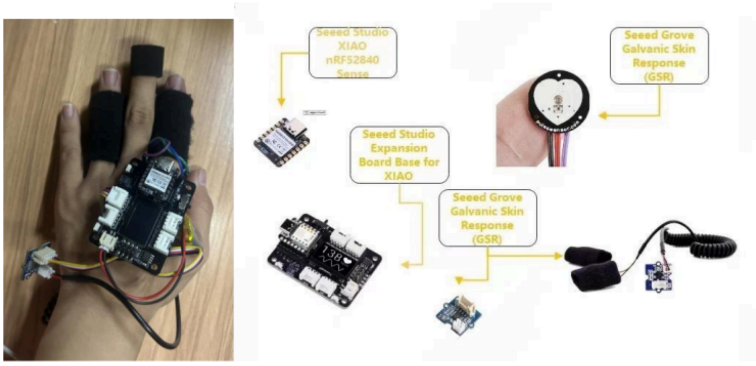

Figure 2. The equipment that the study uses

2.4. Data analysis and processing

In this study, data collected from PPG and EDA sensors, along with questionnaire responses, were subjected to a comprehensive analysis. The analysis involved several key steps: data loading and preprocessing, data smoothing and handling, heart rate calculation, statistical analysis, and correlation analysis. The following sections detail each step, including the methods, tools, and platforms used.

2.4.1. Data loading and preprocessing

Data Source and Tools: The data collected was obtained from CSV files recorded by the PPG and EDA sensor readings and an Excel file for questionnaire responses. Data loading was performed using the Pandas library's 'read_csv()' and 'read_excel()' functions. All code writing and debugging was done in Pycharm.

Data Processing: For PPG data, this study applied a sliding window approach to calculate a rolling average with a window size of 0.75 seconds and a sampling frequency of 100 Hz. Missing values in the rolling average were replaced with the average signal value, and the average was increased by 20% to mitigate the impact of secondary heart contractions [9-12]. A similar approach was used for EDA data, with a smaller window size of 0.1 seconds. The data was standardized by mapping detailed questionnaire items to concise codes and converting columns to numeric values using 'pd.to_numeric()' to handle non-numeric entries appropriately.

2.4.2. Data smoothing and handling

Signal Smoothing: To enhance signal quality and reduce noise, this study applied a rolling average to both PPG and EDA data. A 0.75-second window was used for PPG data, and a 0.1-second window was used for EDA data. The smoothed signals Are visualized using Matplotlib to observe

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temporal variations and ensure that the smoothing process accurately reflects the underlying trends [10-13].

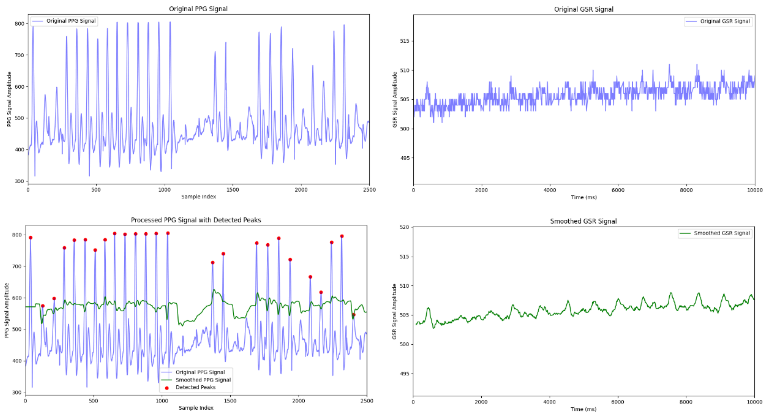

Figure 3. PPG and EDA data processing: raw PPG data is on the top left, processed PPG data is on the bottom left, raw EDA data is on the top right, and processed EDA data is on the bottom right

2.4.3. Heart rate calculation

Processing PPG Data:

The data exhibited minimal noise since the sensor was used in a stable indoor environment. To accurately determine the heart rate from the PPG signal, a peak detection algorithm was used to identify peaks in the PPG data. A sliding window method was applied to compute the average signal over a specific period. This average was then multiplied by a predetermined factor to establish a control value. Peaks exceeding this control value were considered valid heart rate peaks. The time intervals between successive peaks (RR intervals) were measured and converted into milliseconds to calculate the average heart rate in beats per minute (BPM) (see Figure 3). This approach ensures a precise heart rate measurement while filtering out non-significant fluctuations [9-12].

2.4.4. Statistical analysis

Paired t-Test: Paired t-tests were used to assess differences in physiological metrics between mindful and mindless conditions. The means and standard deviations for various metrics (e.g., PPG, EDA) were calculated, and the 'ttest_rel()' function from the 'scipy. stats' library was used to compute t-values and p-values. This analysis determined the statistical significance of differences observed in the data [14,15].

2.4.5. Correlation analysis

Correlation Matrix Calculation: To investigate relationships between questionnaire responses, a correlation matrix was computed using Pearson correlation coefficients with the 'corr()' method from Pandas for all numeric variables.

Heatmap Visualization: The correlation matrix was visualized using Seaborn's heatmap function, which displayed the correlation coefficients with colour coding. This provided an intuitive view of the relationships between variables and detailed the specific correlation values for each pair [16,17].

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2.4.6. Tools and platforms

Python Libraries: The analysis utilized Python libraries, including Pandas, NumPy, Matplotlib, Seaborn, and Scipy, for data manipulation, visualization, and statistical analysis.

Development Environment: PyCharm was used as the integrated development environment (IDE) for all code development and debugging.

This structured approach ensured the accuracy and reliability of the data analysis. The use of these methods and tools provided a robust framework for analyzing the physiological and psychological data collected in the study.

3. Results

The data analysis revealed a statistically significant increase in heart rate variability (HRV) during mindless eating compared to mindful feeding ($p - value\ of\ 0.005 < 0.05$) (see Table 1). This finding suggests that participants experienced lower psychological stress during mindless eating. It implies that heart rate varibility is a better indicator of reduced stress levels in mindless eating. On the other hand, there was not a statistically significant difference in skin conductance between mindless overeating and mindful overeating ($p - value\ of\ 0.052 > 0.05$) (see Table 1).

Table 1. Mindless overeating vs. mindful overeating comparison

	Mindless overeating	Mindful overeating	MeanDiff(95%CI)	T-value	P-value
mean heart rate (beats per minute)	88.47 ± 13.77	100.67 ± 22.58	12.20(4.20,20.19)	3.084	0.005
mean skin conductance (S)	460.38 ± 93.52	492.94 ± 79.83	32.56(0.29,64.80)	2.040	0.052

Analysis of the questionnaire data revealed several key correlations (see Figure 4):

1. Video attractiveness was positively correlated with attention concentration ($correlation = 0.54$).

2. Attention concentration was negatively correlated with mindless eating ($correlation = -0.76$).

3. Mindless eating had a very strong positive correlation with automatic eating ($correlation = 0.89$).

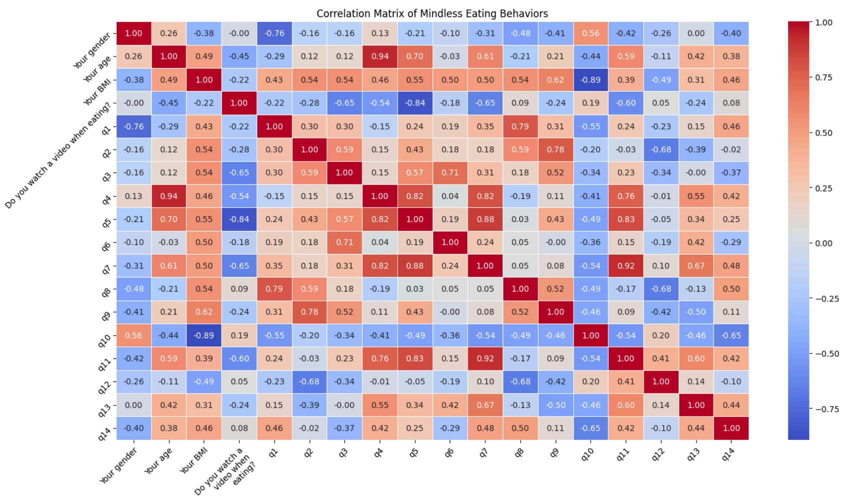

Figure 4. Questionnaire relevance heat map

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These correlations suggest that engaging video content is associated with diverting attention from eating behaviour, which may increase the likelihood of mindless eating. Specifically, more attractive video content correlates with a greater distraction from eating, potentially reducing the awareness of eating actions and promoting automatic consumption. Additionally, the positive correlations between video attractiveness and BMI suggest that individuals with higher BMIs may be more likely affected by video content, which could exacerbate mindless eating behaviours. However, while these correlations are observed, further research is needed to establish a causal relationship.

4. Conclusion

The results indicate that mindless eating is associated with significantly higher HRV than mindful eating. This suggests that individuals experience less psychological stress during mindless eating, which also implies that heart rate variability may be a better indicator of reductions in stress during mindless overeating episodes than mindful overeating episodes. The reduced stress during mindless eating may interfere with normal physiological feedback mechanisms, potentially leading to continued overeating.

These findings are consistent with existing literature, which suggests that external stimuli, such as video content, can significantly impact physiological measures like skin conductance (SC) [18]. The observed variations in SC values may result from the influence of video content, which could introduce variability and affect the interpretation of the results [19]. However, the questionnaire data offers additional insights. The positive correlation between video attractiveness and attention concentration ($correlation = 0.54$) indicates that engaging content can divert attention from eating. This aligns with the sensory-normative model, which posits that external cues significantly impact food intake [5]. The negative correlation between attention concentration and mindless eating ($correlation = -0.76$) supports the notion that distractions reduce the awareness of eating actions, thereby promoting automatic consumption.

The very strong positive correlation between mindless eating and automatic eating (correlation = 0.89) highlights that individuals are more likely to engage in automatic eating when they are less aware of their eating behaviour. This is consistent with previous research showing that automatic eating is prevalent in distracted or mindless eating scenarios [7]. This indicates that distraction can lead to automatic eating behaviour, reinforcing these findings.

The positive correlation between video attractiveness and BMI suggests that individuals with higher BMIs may be more influenced by engaging video content, potentially leading to increased mindless eating [18]. This underscores the importance of managing external variables in physiological studies to ensure accurate conclusions. This finding aligns with research on the role of sensory pleasure in food consumption, which suggests that engaging stimuli can influence eating behaviour [3].

A notable limitation of this study is the relatively small sample size and the limited diversity in participant demographics, such as age, weight, dietary habits, and BMI, which may restrict the generalizability of the findings. Additionally, the subjective selection of video content could introduce bias and affect SC measurements. Future research should address these limitations using larger, more diverse samples and exploring specific demographic factors like age or BMI. Investigating how different BMIs influence mindless eating could provide valuable insights. Incorporating inertial measurement units (IMUs) and developing machine learning models for predictive analysis of mindless eating behaviours could enhance data accuracy and practical application [20]. For instance, understanding the complex interplay between genetic risk, lifestyle, and obesity emphasizes the importance of detailed demographic analysis in studying eating behaviours [2].

In summary, this study highlights the physiological differences between mindless and mindful eating, showing that mindless eating is linked to reduced psychological stress and that heart rate variability is a better indicator to demonstrate reductions in stress. The impact of external distractions, such as engaging video content, on eating behaviour emphasizes the need for interventions to reduce distractions and enhance mindfulness during eating. These insights contribute to a better understanding of mindless eating and offer a foundation for developing strategies to manage overeating and improve overall health.

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