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PERCEPTION OF ARTIFICIAL INTELLIGENCE: GSR ANALYSIS AND FACE DETECTION

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Abstract. This study explored the perception of artificial intelligence (AI) through GSR analysis and facial expression detection across eight different video stimuli. The results indicate that one video elicited the highest cognitive engagement, while another showed significant engagement through both the frequency and intensity of responses. Certain videos displayed a lower frequency but higher intensity of responses. The Shapiro–Wilk and Levene's tests validated the use of ANOVA, confirming the normality and homogeneity of variances. Despite variations in mean GSR peaks per minute, ANOVA revealed no significant differences in physiological responses among the different interaction types. Gender analysis revealed similar high physiological responses to AI stimuli for both males and females, with most stimuli eliciting statistically significant GSR peaks per minute. The Affectiva AFFDEX SDK classifier analysed emotional responses, revealing that joy was predominantly higher in one video, while another elicited the most sadness. Anger and fear were nearly non-existent, and contempt varied, with one video showing the highest response. Disgust and surprise responses were generally low. These findings highlight the importance of emotional content in engaging viewers and the utility of GSR and facial expression analysis in understanding AI's impact on user perception. This research provides insights into cognitive and emotional engagement with AI-related stimuli, emphasizing the need for tailored content to enhance user interaction. The study's implications extend to marketing, education, and healthcare, where optimizing user engagement with AI can lead to improved outcomes and satisfaction.

Keywords*:* emotion; neuromarketing; artificial intelligence; consumer.

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1. Introduction

The rapid advancement of artificial intelligence (AI) technologies has significantly transformed various sectors, including marketing, education, healthcare, and retail. Understanding how users perceive and interact with AI systems is crucial for the successful implementation and acceptance of these technologies. Analysing the perception of AI using GSR analysis and facial expression detection allows gauging users' emotional and physiological responses. In marketing, understanding consumer emotions and reactions is vital for developing effective strategies and enhancing customer engagement. GSR analysis and facial expression detection provide real-time insights into how consumers respond to advertisements, product placements, and overall brand interactions [1–7]. This information can help marketers tailor their strategies to evoke desired emotional responses, ultimately improving customer satisfaction and loyalty.

In the educational sector, AI-driven tools are increasingly used to personalize learning experiences and improve educational outcomes. By analysing students' emotional and physiological responses through GSRs and facial expressions, educators and developers can gain insights into how different teaching methods and content affect student engagement and learning efficiency [8–13]. These data can be used to create more adaptive and responsive educational environments that cater to the diverse needs of learners. In healthcare, AI applications range from diagnostic tools to personalized treatment plans. Understanding patient emotions and stress levels through GSRs and facial analysis can enhance the effectiveness of AI-driven healthcare solutions [14–16]. For instance, monitoring patients' emotional states during telemedicine consultations can provide additional context for healthcare providers, leading to more accurate diagnoses and tailored treatment plans.

In sustainable development, precision agriculture leverages AI to optimize the use of water, fertilizers, and pesticides, leading to higher yields and reduced environmental impact. Climate modelling with AI processes vast amounts of data to predict weather patterns and climate changes more accurately, aiding policymakers in creating effective adaptation and mitigation strategies [17–20]. Wildlife conservation benefits from AI-powered tools such as camera traps with image recognition software, which monitor wildlife populations and poaching activities, facilitating targeted conservation efforts. Smart cities utilize AI to optimize energy use, waste management, and transportation systems, such as managing traffic flow to reduce congestion and emissions or optimizing waste collection routes. In green development, AI enhances energy efficiency by analysing usage patterns to suggest energy-saving measures and automated systems, reducing waste in buildings and industries [21–25]. Sustainable supply chains are improved with AI tracking and analysing data to ensure sustainable sourcing and lower carbon footprints, while more accurate demand predictions reduce waste and improve logistics efficiency. Renewable energy forecasting is made more precise with AI, balancing supply and demand and reducing reliance on fossil fuels. Environmental monitoring is also enhanced as AI processes data from sensors that are used to monitor air and water quality, deforestation, and pollution levels, allowing for prompt mitigation actions. AI-driven tools are pivotal in the energy transition, particularly in grid management, where AI optimizes the operation of electrical grids by integrating renewable energy sources and ensuring a stable supply through demand prediction and generation adjustments [26–29]. Battery storage management benefits from AI, which manages charging and discharging cycles to extend battery life and improve efficiency and is crucial for storing intermittent renewable energy. Smart metering with AI provides detailed insights into energy consumption, helping consumers and utilities manage energy use efficiently and reduce peak demand. In carbon capture and storage, AI optimizes processes and identifies the best locations and methods for capturing and storing carbon dioxide. Additionally, electric vehicles (EVs) are optimized by AI for efficient operation and charging, including route planning for optimal battery use and integrating EVs with the grid to stabilize supply and demand. These AI-driven tools are essential for achieving sustainability goals, promoting green development, and facilitating the transition towards a cleaner, more efficient future.

AI-driven tools are revolutionizing economic development and human resources management, offering innovative solutions to enhance efficiency and decision-making [30–34]. In economic development [35–38], AI-powered analytics play a significant role by processing vast amounts of economic data to identify trends, forecast growth, and inform policy decisions. These insights enable governments and organizations to allocate resources more effectively, stimulate economic activity, and address socioeconomic challenges. AI also drives financial inclusion by leveraging machine learning algorithms to assess creditworthiness and provide microloans to underserved populations, fostering entrepreneurship and economic empowerment.

In the retail industry, integrating AI with neuromarketing techniques helps improve both customer experiences and employee satisfaction. By analysing physiological and emotional data, retailers can design store layouts, product displays, and customer service interactions that maximize positive emotional responses [39–46]. Additionally, understanding employees' emotional states can lead to improved working conditions and productivity.

While the benefits of using GSR analysis and facial expression detection are clear, it is also essential to address ethical and privacy concerns. Ensuring that data are collected and used transparently and ethically is crucial for maintaining user trust and compliance with privacy regulations [47]. Researchers and developers must implement robust data protection measures and provide clear communication about how biometric data will be used.

The topicality of studying AI perception using GSR analysis and facial expression detection lies in its ability to provide deep, real-time insights into user emotions and physiological responses. This paper aims to examine the perception of artificial intelligence by applying GSR analysis and face detection, which justifies the originality of the research.

This paper has the following structure: literature review explores the theoretical framework of using GSR analysis and face detection in investigating the perception of artificial intelligence; Materials and Methods describe the process of the experiment for data collection and instruments for quantitative analysis; Results and Discussion explain the results of the analysis; and Conclusion summarises the core results, policy implications, limitations and directions for further research.

2. Literature Review

The perception of artificial intelligence in various contexts has garnered significant research interest, particularly focusing on physiological and emotional responses using methods such as GSR analysis and facial expression detection. Chen et al. [7] examined the emotional dynamics of young children during math problem-solving activities through a multimodal study, combining GSR analysis and facial expression detection to track emotional responses and reveal how these fluctuations impact learning processes. Crescenzi-Lanna [48] highlighted the critical role of AI technologies in examining educational outcomes for young children, while Di Mitri et al. [49] emphasized their importance in converting raw data into actionable insights within multimodal learning analytics frameworks. Emerson et al. [50] demonstrated the utility of these methods in game-based learning, showing how AI-driven tools can provide nuanced insights into student engagement. Que et al. [51] studied the emotional impact of background music on reading comprehension using facial expression detection to optimize learning environments. Wiedbusch et al. [52] focused on supporting teachers' interpretation of engagement data through AI-powered dashboards, highlighting the practical applications of these technologies in everyday educational practices. Feng et al. [13] investigated collaborative learning using multimodal learning analytics, integrating video coding and EEG data mining to observe student interactions and emotional responses, providing insights into how AI can enhance collaborative learning environments. Hasnine et al. [53] focused on extracting and visualizing students' emotions to detect engagement in online learning, utilizing GSR analysis and facial expression detection to monitor and improve student engagement with AI-based learning platforms. Martin et al. [54] introduced computationally augmented ethnography to track emotions and learning in museum games, employing facial expression detection to analyse visitors' emotional responses to AI-driven educational games. Mu et al. [55] conducted a systematic review on multimodal data fusion in learning analytics, emphasizing the integration of GSR analysis and facial expression detection to provide a comprehensive understanding of learner emotions and behaviours. Que & Hu [56] investigated the effects of background music on visual cognitive tasks using multimodal learning analytics, incorporating facial expression detection to assess the emotional impact of background music on task performance.

Ahmed et al. [1] explored the neuromarketing concept within artificial neural networks, specifically forecasting and simulation in the advertising industry, emphasizing the importance of understanding consumer emotional responses using GSR analysis to measure arousal levels. Al-Nafjan et al. [57] conducted a systematic review on neuro-tourism, discussing how GSR analysis can measure tourists' emotional and physiological responses to various stimuli and highlighting its potential to capture authentic emotional reactions. Attié et al. [47] proposed ethical guidelines for neuromarketing 2.0, incorporating AI and GSR analysis to ensure consumer well-being, underscoring ethical considerations and the need for transparency in collecting and analysing physiological data. Bansal & Gupta [7] focused on integrating AI into neuromarketing, utilizing GSR analysis to enhance emotional branding and sensory marketing strategies, arguing that understanding GSR data can help marketers tailor more effective campaigns. Bhandari [58] reviews neuromarketing trends and opportunities, emphasizing the role of GSR analysis in capturing real-time emotional responses and discussing how companies can leverage these data to gain deeper insights into consumer behaviour. In terms of facial expression detection, Avinash et al. [59] investigated its use in neuromarketing, specifically examining the frontal theta asymmetry induced by musical stimuli, highlighting its potential in understanding consumer emotional states. Bello et al. [60] utilized adaptive vector models to identify emotional patterns in audiovisual advertising through facial expression detection, demonstrating the method's effectiveness in capturing nuanced emotional responses. Ferruz-González et al. [61] analysed the Cruzcampo campaign using facial expression detection to measure emotional engagement, illustrating how facial analysis can provide valuable insights into the impact of advertising on consumer emotions. Filipovic et al. [62] applied AI to detect emotions in neuromarketing by combining facial expression detection with other biometric signals, highlighting the synergy between AI and facial analysis. Gagliardi et al. (2023) used contrastive learning to improve neural networks for emotion recognition, emphasizing the role of facial expression detection and suggesting that integrating domain knowledge can enhance accuracy. Integrating GSR and facial detection, Jaramillo et al. [63] focused on the automatic identification of emotional patterns in audiovisual advertising using both methods, demonstrating their complementary nature.

One study [64] integrated explainable AI (xAI) with neuromarketing, using fMRI data alongside GSR and facial analysis to understand brand perception, highlighting the potential for AI to provide deeper insights into consumer behaviour. Nagya et al. [65] explored predicting arousal using machine learning of EEG signals, integrating GSR and facial expression detection to enhance the accuracy of emotional predictions. Ramirez et al. [66] classified "like" and "dislike" decisions using EEG and fNIRS signals complemented by GSR and facial expression data, illustrating the potential of combining these methods to predict consumer preferences more accurately. Ge et al. [67] conducted a mixed-methods study on learning at disturbance in experienced designers utilizing these technologies to capture emotional and cognitive responses to disruptions in the design process. Giannakos & Cukurova [68] emphasize the role of learning theory in multimodal learning analytics, advocating for the integration of GSRs and facial expression data to enhance theoretical frameworks and practical applications. Hasnine et al. [69] explored classroom monitoring using emotional data, demonstrating how these tools can improve real-time understanding of student engagement and emotional states.

Hassan et al. [70] introduced the EZ-MMLA toolkit, which simplifies the collection of multimodal data streams, including GSRs and facial expressions, making these powerful analytics accessible to educators and researchers. Järvelä et al. [71] focused on predicting regulatory activities to optimize collaborative learning, leveraging these technologies to understand and enhance social regulation among learners. Kubsch et al. [72] discussed the importance of emotions in multimodal learning analytics, highlighting how GSR and facial detection can provide insights into the emotional dimensions of learning. Sinha [73] examined the impact of emotions on problem-solving followed by instruction using multimodal analytics to provide explanatory accounts of emotional responses. Song et al. [74] presented a holistic visualization solution for understanding multimodal data within an educational metaverse platform, incorporating GSR and facial expression analysis to enrich the learning experience. Xu et al. [75] analysed collaborative patterns during pair programming in higher education, employing these technologies to gain insights into the emotional and cognitive dynamics of collaboration. Zhu et al. [76] explored the emotional and cognitive dynamics of knowledge building in young students using GSR and facial expression detection to track and enhance the learning process.

Caratù [39] examined the integration of AI, neuromarketing, and smart-retail technologies to enhance employees' comfort and service efficiency by analysing physiological and emotional responses. Costa-Feito & Blanco-Moreno [77] investigated healthy food consumption using neuromarketing and AI to predict consumer behaviour through GSRs and facial expressions.

De la Peña et al. [78] discussed AI and neuromarketing in enodiplomacy, using GSR and facial analysis to enhance regional product marketing and cultural preservation in the face of climate change. Gagliardi et al. [79] leveraged contrastive learning and domain-specific knowledge to improve neural networks for emotion recognition by combining computational methods with biometric data. Kaur et al. [14] focused on cognitive emotion measures of the brain, utilizing EEG, facial expression detection, and GSR to understand emotional responses. Lei et al. [80] address the challenges of predicting consumer behaviour using neuromarketing tools, reviewing the current status, and proposing future research directions. Lisun et al. [81] examine the role of social networks in shaping consumer trends by using AI and neuromarketing to analyse social media interactions and predict behaviour through emotional responses. Piazza et al. [82] empirically evaluated design strategies to increase affective customer responses on e-commerce pages using GSR and facial expression analysis. Taqwa et al. [83] explored the naïve Bayes method for predicting purchasing decisions by applying it to physiological data from a neural impulse actuator. The abovementioned results underscore the importance of integrating biometric measures with AI to gain deeper insights into consumer behaviour, enhance predictive accuracy, and optimize marketing and educational strategies by understanding cognitive and emotional responses.

3. Materials and Methods

3.1. Data collection

The data for this study were obtained during an experiment conducted at Sumy State University in Ukraine. The focus group included 24 respondents, which included students (at all levels) and researchers at Sumy State University. The social and demographic parameters of the respondents are presented in Table 1.

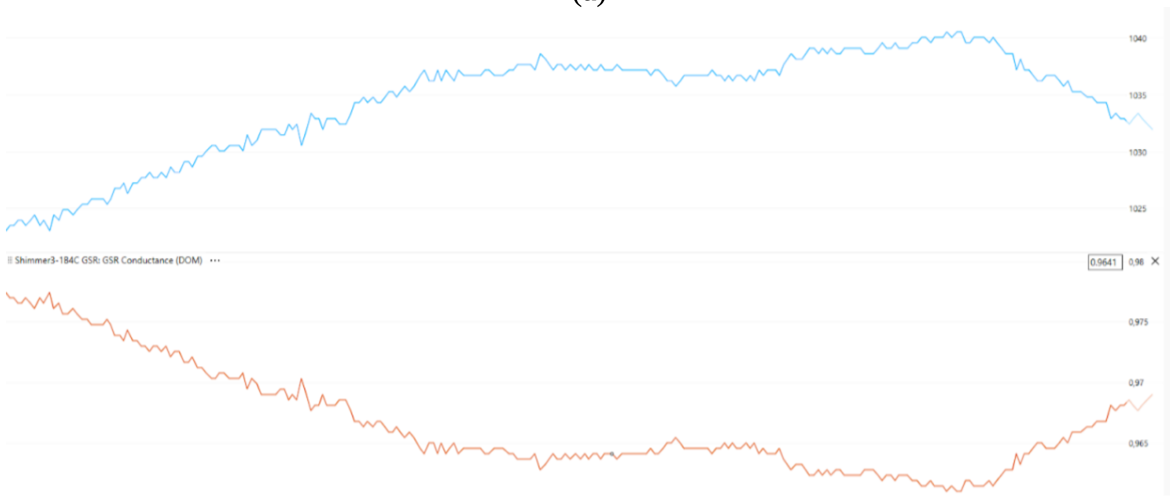
Table 1. Social and demographic portraits of the respondents

Demographic characteristics	Scale	Number	Share, %	Max	Min
Age	18 – 35 years old	19	79.2%	53	18
	Over 35 years old	5	20.8%		
Role in the University	Student	18	75.0%	1	2
	Researchers	6	25.0%		
Gender	Male	5	20.8%	1	2
	Female	19	79.2%		

Source: Developed by the authors.

This experiment was meticulously designed using iMotions 10.0 software, which integrates Shimmer 3 devices for GSR analysis and a web camera for facial expression analysis through Affectiva AFFDEX technology. In the experimental setup, each respondent individually viewed a series of videos on a computer equipped with a web camera. The web camera continuously captured their facial expressions, which were analysed in real time using Affectiva AFFDEX to detect and quantify emotional responses. Simultaneously, each respondent was connected to three sensors of the Shimmer 3 device, which monitored their physiological responses by measuring the GSR. This dual approach provided a comprehensive view of both emotional and physiological reactions to the stimuli. The figure illustrates the placement of the sensor on the study participant and the process of data collection via iMotion software from all sensors during the setup phase for a single subject.

(a)



(b)

Figure 1. (a) Placement of GSR sensors; (b) Monitoring streaming data
Source: Developed by the authors.

The experiment featured a series of short videos focusing on the role of artificial intelligence in human development, which is split from the movie of BBC Ukraine – Oleg Karpyak's "Superhuman artificial intelligence. How "it" works and what it all leads to" (https://youtu.be/sUG-L87RxZs?si=IUbgiVn0gEIkVNKA). The videos have different types of video dubbing and content (static and dynamic, text in the video, human, music) created by human or/and artificial intelligence. The detailed explanations of the stimuli (video, questions) are shown in Table 2.

Table 2. Video stimuli of the investigations and their characteristics

Code name of video stimuli	Emotional contrast	D	Characteristics									
			Generated by AI					Generated by human				
			V	P	T	M	VD	V	P	T	M	VD
VS 1	positive	44	+	+	no	no	no	+	no	no	no	+
VS 2	positive	20	+	+	no	no	no	no	+	no	no	+
VS 3	patriotism, positive	36	no	no	+	no	+	+	+	no	+	+
VS 4	humour, positive	49	+	no	+	no	+	+	+	no	no	+
VS 5	positive	26	no	+	no	no	no	no	no	no	no	+
VS 6	surprise, positive	35	+	no	+	no	no	+	no	no	no	+
VS 7	surprise, positive	34	+	no	no	no	no	no	no	no	no	+
VS 8	surprise, negative	75	+	+	+	no	+	+	+	no	no	+

Note: V – video; P – picture; T – text; M – music; VD – video dubbing; EC – emotional contrast; D – duration (s); + – contain; no – does not contain.
Source: Devised by the authors.

Following each video segment, respondents were asked relevant questions to gauge their understanding and perceptions. This allowed for the collection of both quantitative and qualitative data, enriching the overall analysis.

The total duration of video stimuli presented during the experiment was meticulously recorded, amounting to 319 seconds. This precise measurement ensured that the timing of responses could be accurately correlated with specific stimuli, providing deeper insights into the participants' reactions.

3.2. Methods
3.2.1. GSR measurement

At the premier stage of the study, GSR analysis was employed to identify participants' perceptions of AI. The GSR measures the skin's electrical conductance, which varies with its moisture level, indicating physiological arousal. The quality of the GSR signals was assessed using two primary metrics: the signal-to-noise ratio (SNR) in decibels and the percentage of missing signals. The SNR is a measure that indicates the amount of signal relative to noise in a time series or signal. It is defined as the ratio of the signal power to the noise power and is expressed in decibels (dB):

$$SNR = 10\ log_{10}(\frac{P_{signal}}{P_{noise}}) \quad (1)$$

where P_{signal} is the power of the signal and P_{noise} is the power of the noise.

An SNR greater than 1:1 (above 0 dB) indicates that the signal surpasses the noise, implying that the recorded physiological response stands out sufficiently from background noise, thereby making the data reliable for analysis. On the other hand, a negative SNR means that noise

dominates the signal, suggesting poor signal quality and potentially unreliable data for drawing accurate conclusions. A SNR above 20 dB is considered sufficient to ensure good signal quality. Signals with SNRs exceeding 20 dB typically have less than 1% noise, meaning that most of the data are composed of signals rather than noise. In this range, when the SNR falls between 0 and 20 dB, the signal is not significantly stronger than the noise, which can lead to ambiguous or less reliable data. To accurately assess data quality in this intermediate range, evaluating the proportion of missing signals is crucial. This involves checking the completeness and integrity of the data. High percentages of missing signals can indicate data loss or corruption, complicating the analysis and interpretation of GSR measurements.
After screening and validating the quality of the GSR signal, 13 respondents were excluded from further analysis. The cleaned respondents for whom the GSR signal was affordable are shown in Table 3.

Table 3. Quality of the GSR signal within the video stimuli and respondents

Respondent code	Characteristics	Video Stimuli (VS)							
		1	2	3	4	5	6	7	8
R01	SNR	33.47	22.67	30.2	31.06	34.4	25.7	26.52	28.95
	SM	0	0	0	0	0	0	0.02	0
R04	SNR	33.5	36.78	31.24	35.02	35.65	34.02	27.34	32.92
	SM	0	0	0	0	0	0	0	0
R06	SNR	36.87	11.57	36.38	25.38	24.28	35.72	39.33	22.98
	SM	0	58.86	18.79	31.42	20.4	8.44	27.91	45.33
R09	SNR	24.24	39.21	34.17	35.91	38.01	30.38	28.07	40.88
	SM	0	0	0	0	0	0	0	0
R10	SNR	33.25	39.49	42.8	46.96	35.83	34.12	42.33	48
	SM	0	0	0.02	0	0	0	0	0
R11	SNR	24.37	18.38	36.17	32.4	39.1	20.49	24.13	30.39
	SM	0	0	0	0	0	37.17	38.74	58.94
R15	SNR	27.39	25.6	29.76	33.91	34.04	27.92	14.82	32.87
	SM	0	0	0	0	0	0.22	0	0.01
R17	SNR	33.23	8.16	24.04	30.26	28.01	28.21	30.71	23.94
	SM	0	0	0	0	0	0	0.02	0
R18	SNR	20.08	27.74	33.01	25.94	22.26	31.91	32.2	20.08
	SM	0	0.02	0	0	0	0.23	0	0
R19	SNR	31.78	33.35	32.55	32.15	33.63	23.05	24.34	27.43
	SM	0	0	0	0	0.03	0	0	0.02
R22	SNR	29.64	26.12	22.16	21.55	32.37	27.47	28.47	27.86
	SM	0.02	0	0	0	0	0	0.02	0.01

Note: SNR – signal-to-noise ratio; SM – missing signal (%).
Source: Devised by the authors.

Each participant's responses to a given stimulus or scene were evaluated using several metrics. First, the peak count represents the total number of detected peaks during the stimulus or scene. Second, the peaks per minute are calculated by dividing the total number of peaks by the duration of the stimulus or scene and expressing this as peaks per minute. Finally, the average peak amplitude measures the average amplitude of the detected peaks during the stimulus or scene.

3.2.2. AFFDEX

Affectiva AFFDEX analysis is applied to analyse facial expressions and determine emotional responses to relevant stimuli. This technology utilizes advanced algorithms to detect and measure minute changes in facial expressions, providing a detailed understanding of participants' emotional states. By capturing real-time data, the analysis can distinguish between a range of emotions, such as joy, sadness, anger, surprise, contempt, and disgust. This granular level of emotional analysis allows researchers to correlate specific emotional responses with particular segments of video stimuli. For instance, if a video segment is intended to evoke positive emotions such as joy or amusement, the Affectiva AFFDEX analysis allows the effectiveness of the content to be validated by quantifying the percentage of time participants display these emotions. Conversely, for content that might address serious or concerning topics, the analysis can detect and measure negative emotions such as sadness or fear. This approach provides comprehensive insights into how different elements of video stimuli, such as visuals, text, and audio, contribute to the overall emotional impact.

3.2.3. Data analysis

Statistical analysis of the physiological signals recorded from each individual was conducted using ANOVA (analysis of variance). This analysis aimed to compare the differences in signals across various stimuli for each participant. The ANOVA method combined with the Shapiro–Wilk W test for assessing data normality and Levene's test for homogeneity of variances was selected due to its robustness in handling time series data. Several key statistical measures were employed to assess the variability in detecting changes in GSR among the diverse participants: the mean was used to determine the average response amplitude for each stimulus, and the standard deviation was used to measure the dispersion of the response amplitudes from the mean, indicating the consistency of responses. Data processing and visualization were performed using the statistical software Stata.

4. Results and Discussion

The analysis of participants' cognitive engagement, reflected through GSR peaks per minute and average peak amplitude, is presented in Table 4.

Table 4. Descriptive statistics of cognitive engagement metrics

Label	Peaks Per Minute		Average Peak Amplitude		Freq.
	Mean	Std. dev.	Mean	Std. dev.	
VS 1	4.3663636	2.6632509	0.03069091	0.04733729	11
VS 2	4.3536364	3.6332637	0.0351	0.04945954	11
VS 3	3.3054545	2.7396217	0.03499091	0.05544001	11
VS 4	3.1054545	2.207063	0.04533636	0.06770467	11
VS 5	4.2281818	2.5063392	0.04862727	0.06824049	11
VS 6	3.25	2.5793255	0.03126364	0.04729339	11
VS 7	3.1572727	2.7783128	0.04833636	0.08179987	11
VS 8	2.9218182	2.3919859	0.04833636	0.04866441	11
Total	3.5860227	2.6688788	0.04033523	0.05753144	88

Note: Std. dev. – standard deviation; Freq. – frequency.
Source: Developed by the authors.

The video stimulus VS 1 elicited the highest average frequency of cognitive engagement, with the most peaks per minute. This suggests that VS 1 was particularly effective in maintaining participant attention and eliciting consistent physiological responses. VS5 also demonstrated significant cognitive engagement, characterized by both a high frequency and high intensity of responses (mean peaks per minute = 4.23, mean average peak amplitude = 0.049 μS). This makes VS 5 another critical interaction type for inducing strong participant reactions. Interaction types such as VS 4 and VS 7 displayed a lower frequency but higher intensity of responses, indicating that while participants responded less often, their responses were notably strong when they did.

The distribution of GSR peaks per minute for each interaction type is presented in Figure 2 using box plots. This visualization provides a detailed view of the frequency of physiological responses elicited by each video stimulus, highlighting the variability and central tendency of participants' cognitive engagement. The box plots display the interquartile range (IQR), containing the middle 50% of the data, with the median line indicating the central value of GSR peaks per minute for each interaction type. Whiskers extend from the boxes to show the range of the data, excluding outliers, which are plotted as individual points outside the whiskers.

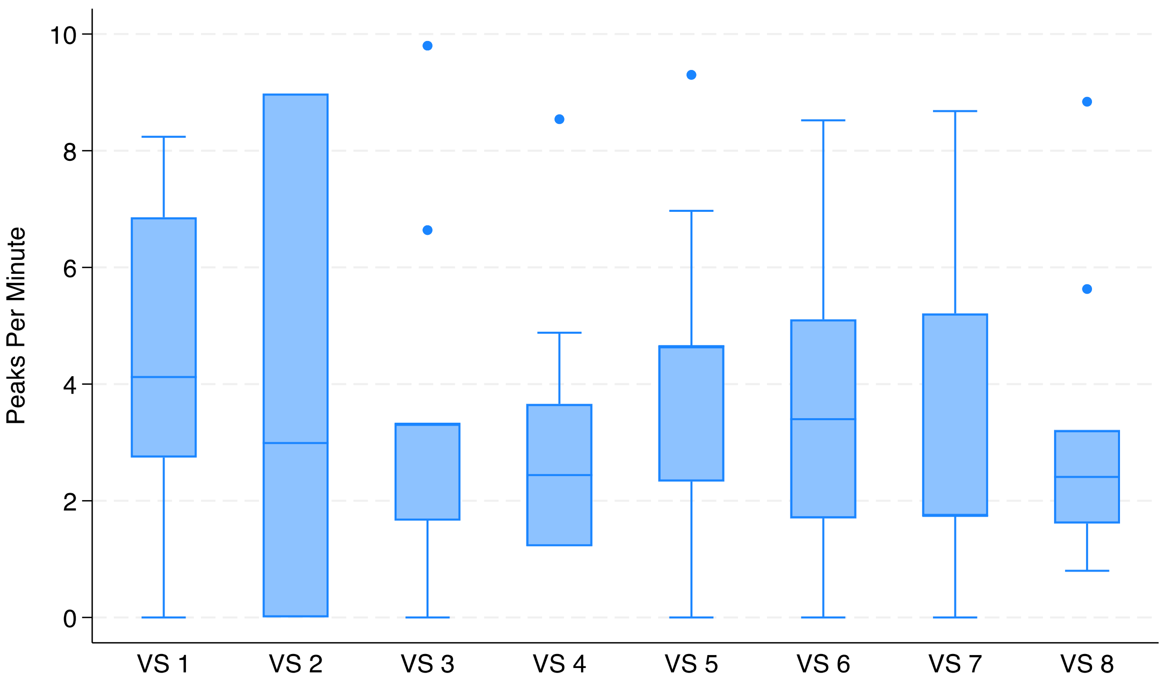


Figure 2. Distribution of GSR peaks per minute for each interaction type
Source: Developed by the authors.

The median GSR peaks per minute for the different interaction types varied, with VS 1 and VS 5 showing higher medians, indicating that these stimuli elicited the most frequent cognitive engagement. The IQRs for these interaction types ranged broadly, reflecting significant variability in participant responses. For instance, VS 1 had an IQR extending from approximately 2.2 to 6.5 peaks per minute, while the whiskers stretched from approximately 0.5 to 8.0 peaks per minute, with a few outliers above this range. Similarly, VS 5 exhibited a high frequency and intensity of responses, with outliers indicating exceptionally high engagement for some participants. The other interaction types, such as VS 2, VS 3, and VS 4, also showed varying degrees of engagement, with lower medians and broader distributions. VS 8 had the lowest median but still displayed relatively high-intensity responses for certain participants. Outliers across all interaction types suggest that a few participants had notably stronger reactions than the overall group.

The Shapiro–Wilk test was used to assess whether the data for each interaction type were normally distributed. The results are summarized in Table 5. The W statistic from the Shapiro–Wilk test indicates how close the distribution is to normal, with values closer to 1 suggesting a normal distribution. Additionally, the p value (prob > z) shows the probability that the data follow a normal distribution, with values less than 0.05 indicating nonnormality.

Table 5. Shapiro–Wilk W test for normal data

Stimuli	Obs	W	V	z	Prob>z
VS 1	11	0.93624	1.032	0.057	0.47736
VS 2	11	0.99216	0.127	-3.124	0.99911
VS 3	11	0.87504	2.023	1.341	0.08997
VS 4	11	0.90394	1.555	0.819	0.20639
VS 5	11	0.98209	0.290	-1.989	0.97664
VS 6	11	0.92906	1.149	0.250	0.40138
VS 7	11	0.92106	1.278	0.447	0.32754
VS 8	11	0.81406	3.010	2.186	0.01441

Note: W – W statistic; V – V statistic; z – z statistic; Prob>z – p value.
Source*:* Developed by the authors.

The results show that for most interaction types (VS 1 to VS 7), the data do not significantly deviate from normality, as their p values are greater than 0.05. Specifically, VS 1 had a W value of 0.93624 and a p value of 0.47736, while VS 2, with a W value of 0.99216, had a p value of 0.99911, indicating a very close fit to a normal distribution. VS 3, VS 4, and VS 5 also showed no significant deviation from normality, with W values of 0.87504, 0.90394, and 0.98209, respectively, and corresponding p values of 0.08997, 0.20639, and 0.97664, respectively. Similarly, VS6 and VS7, with W values of 0.92906 and 0.92106, had p values of 0.40138 and 0.32754, respectively, suggesting that these datasets are normally distributed. However, the data for VS 8 significantly deviated from normality, with a W value of 0.81406 and a p value of 0.01441, indicating a nonnormal distribution.

Levene's test was conducted to assess the homogeneity of variances across different interaction types (Table 6). The results indicate that the variances are consistent and comparable across the groups.

Table 6. Levene's test

Statistic	Pr>F
W0=1.05221702	0.40207069
W50=0.72277924	0.6530024
W10=1.03400284	F=0.414237

Note: W0, W50, and W10 are the mean, median, and 10% trimmed mean, respectively.
Source*:* Developed by the authors.

Specifically, the test statistic for the mean (W0) had a value of 1.05221702 and a p value of 0.40207069, suggesting no significant difference in variances when considering the mean. Similarly, the test statistic for the median (W50) showed a value of 0.72277924 with a p value of 0.6530024, indicating no significant difference in variances when using the median. The test statistic for the 10% trimmed mean (W10) also supported this finding, with a value of 1.03400284 and a p value of 0.414237, suggesting no significant difference in variance.

The p values for all three statistics were greater than 0.05, indicating that the assumption of homogeneity of variances holds. The outputs of Shapiro–Wilk and Levene's tests validate the use of ANOVA for comparing the means of the interaction types, confirming that the variances are homogeneous across the groups. Figure 3 illustrates the mean predicted level of GSRs per minute for various stimuli, providing an overview of how different video stimuli affect the frequency of physiological responses and indicate cognitive engagement.

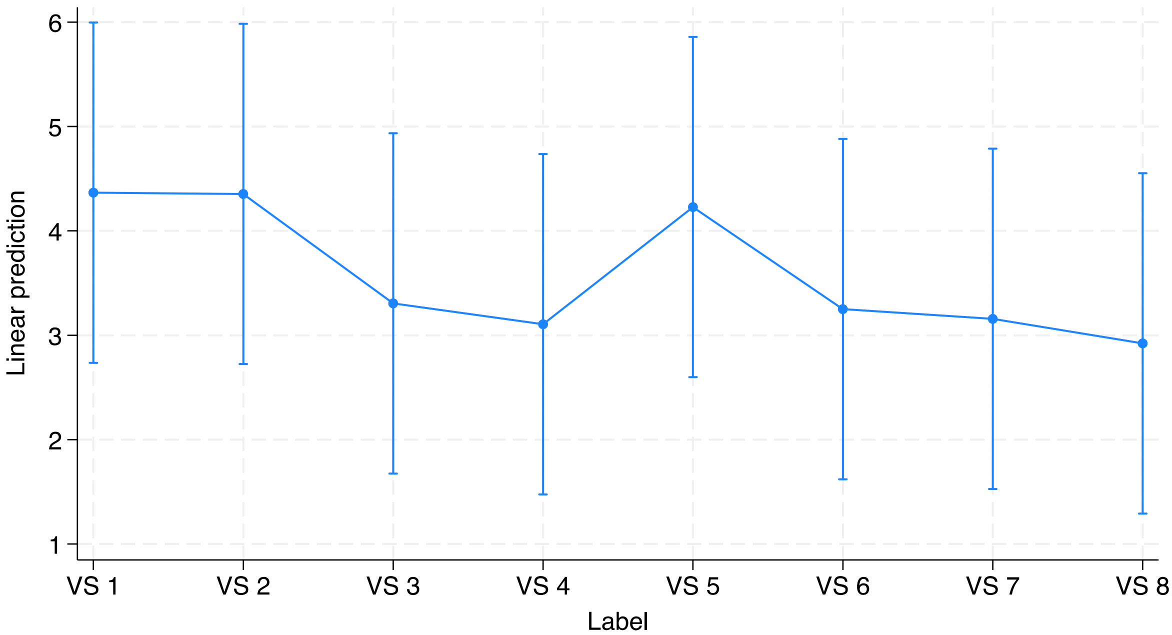


Figure 3. Mean predicted level of GSR peaks per minute by stimuli
Source: Developed by the authors.

Despite the differences in mean values among the stimuli, the ANOVA results indicated that there was no significant association between the GSR peaks per minute and the interaction types, as all p values were greater than the 10% significance threshold. The data indicate that the various AI-related stimuli presented to participants did not cause significant differences in their physiological responses, as measured by GSR peaks per minute.

The delta method was used to estimate the standard errors and confidence intervals for each stimulus's predicted means of GSR peaks per minute (Table 7).

Table 7. Average marginal effects by stimuli

Stimuli	Delta-method					
	Margin	**Std. Err.**	**t**	**P>t**	**[95% conf.**	**interval]**
VS 1	4.366364	0.8191281	5.33	0.000	2.736247	5.996481
VS 2	4.353636	0.8191281	5.31	0.000	2.723519	5.983753
VS 3	3.305455	0.8191281	4.04	0.000	1.675338	4.935571
VS 4	3.105455	0.8191281	3.79	0.000	1.475338	4.735571
VS 5	4.228182	0.8191281	5.16	0.000	2.598065	5.858299
VS 6	3.25	0.8191281	3.97	0.000	1.619883	4.880117
VS 7	3.157273	0.8191281	3.85	0.000	1.527156	4.78739
VS 8	2.921818	0.8191281	3.57	0.001	1.291701	4.551935

Source: Developed by the authors.

For all stimuli (VS 1 to VS 8), the p values are less than 0.05, ranging from 0.000 to 0.001. The statistical significance of these findings indicates that the variations in cognitive engagement levels are not due to random chance. Instead, they are influenced by the specific characteristics of the stimuli presented to the participants. Furthermore, the ANOVA results indicate that variations in cognitive engagement levels for different stimuli by gender are not significant (Figure 4). This means that both male and female participants demonstrated similar high physiological responses to AI stimuli.

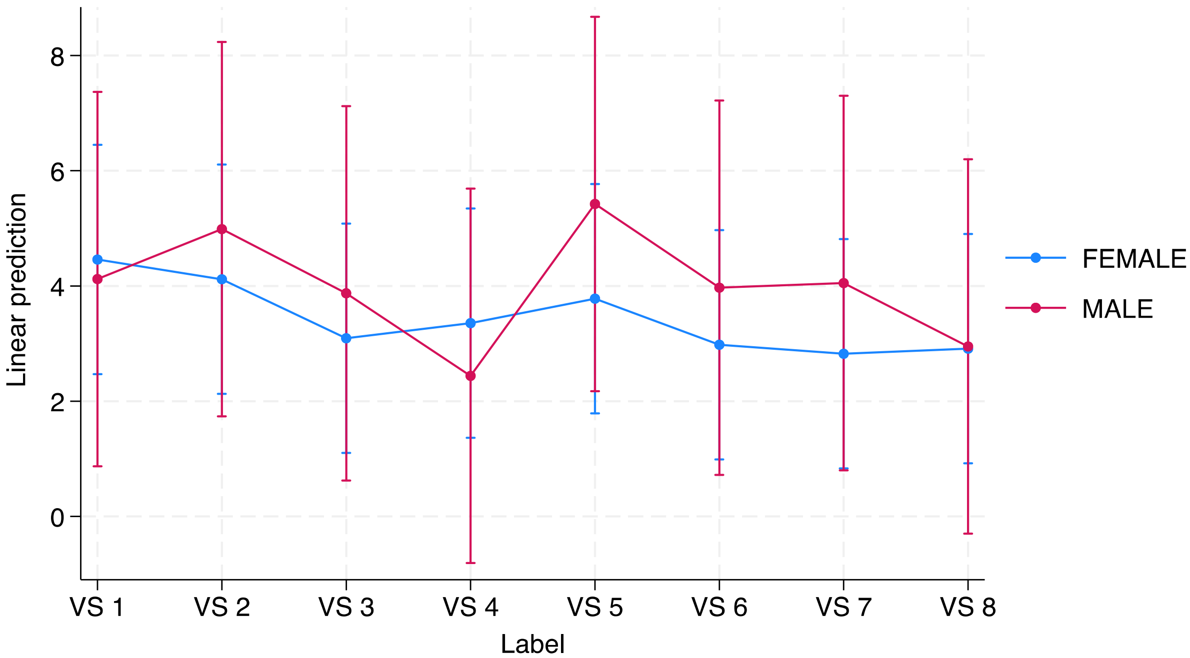


Figure 4. Mean predicted level of GSR peaks per minute by stimuli and gender
Source: Developed by the authors.

Table 8 presents the average marginal effects of GSR peaks per minute elicited by different AI-related stimuli among male and female participants.

Table 8. Average marginal effects by stimuli and gender

Stimul#Gender	Delta-method					
	Margin	std. err.	t	P>t	[95% conf. interval]	
VS 1#female	4.45875	0.9983257	4.47	0.000	2.468624	6.448876
VS 1#male	4.12	1.630259	2.53	0.014	0.8701379	7.369862
VS 2#female	4.11625	0.9983257	4.12	0.000	2.126124	6.106376
VS 2#male	4.986667	1.630259	3.06	0.003	1.736805	8.236529
VS 3#female	3.0925	0.9983257	3.1	0.003	1.102374	5.082626
VS 3#male	3.873333	1.630259	2.38	0.02	0.6234712	7.123195
VS 4#female	3.355	0.9983257	3.36	0.001	1.364874	5.345126
VS 4#male	2.44	1.630259	1.5	0.139	-0.8098621	5.689862
VS 5#female	3.78	0.9983257	3.79	0.000	1.789874	5.770126
VS 5#male	5.423333	1.630259	3.33	0.001	2.173471	8.673195
VS 6#female	2.98	0.9983257	2.98	0.004	0.989874	4.970126
VS 6#male	3.97	1.630259	2.44	0.017	0.7201379	7.219862
VS 7#female	2.8225	0.9983257	2.83	0.006	0.832374	4.812626
VS 7#male	4.05	1.630259	2.48	0.015	0.8001379	7.299862
VS 8#female	2.91125	0.9983257	2.92	0.005	0.921124	4.901376
VS 8#male	2.95	1.630259	1.81	0.075	-0.2998621	6.199862

Source*:* Developed by the authors.

For stimuli VS 1 and VS 2, the mean GSR peaks per minute were 4.45875 for females and 4.12 for males for VS 1 and 4.11625 for females and 4.986667 for males for VS 2. Both genders showed significant engagement with these stimuli. Similarly, for VS 3, the mean GSR peaks per minute are 3.0925 for females and 3.873333 for males, again showing significant engagement for both genders. In the case of VS 4, females had a mean GSR peak per minute of 3.355, indicating significant engagement, whereas males had a mean of 2.44, which was not statistically significant ($p = 0.139$). For VS 5, both genders show significant engagement, with means of 3.78 for females and 5.423333 for males. For VS 6 and VS 7, both genders showed significant responses, with VS 6 having a mean of 2.98 for females and 3.97 for males and VS 7 having a mean of 2.8225 for females and 4.05 for males. Finally, for VS 8, females show significant engagement, with a mean of 2.91125, while males have a mean of 2.95, which is marginally nonsignificant (p value = 0.075). The results indicate that both male and female participants demonstrated similar high physiological responses to most AI stimuli, with most stimuli eliciting statistically significant GSR peaks per minute for both genders. This suggests that the type of interaction significantly impacts cognitive engagement across genders, although there are slight variations in response levels between males and females for specific stimuli.

The Affectiva AFFDEX SDK classifier provided active frames of various emotions (e.g., anger, sadness, disgust, surprise, contempt, and joy) for each video stimulus (Figure 5). Anger was not detected in any of the video stimuli (VS1 to VS8), indicating that none of the videos elicited a significant anger response from the participants. Contempt was present to varying degrees, with VS6 eliciting the highest response (5.88%) and VS1 the lowest (0.41%). Disgust responses were generally low, with notable responses in VS1 (1.70%) and lower to no responses in other videos. Fear was almost non-existent across the videos, with a minor response recorded only in VS6 (0.66%).

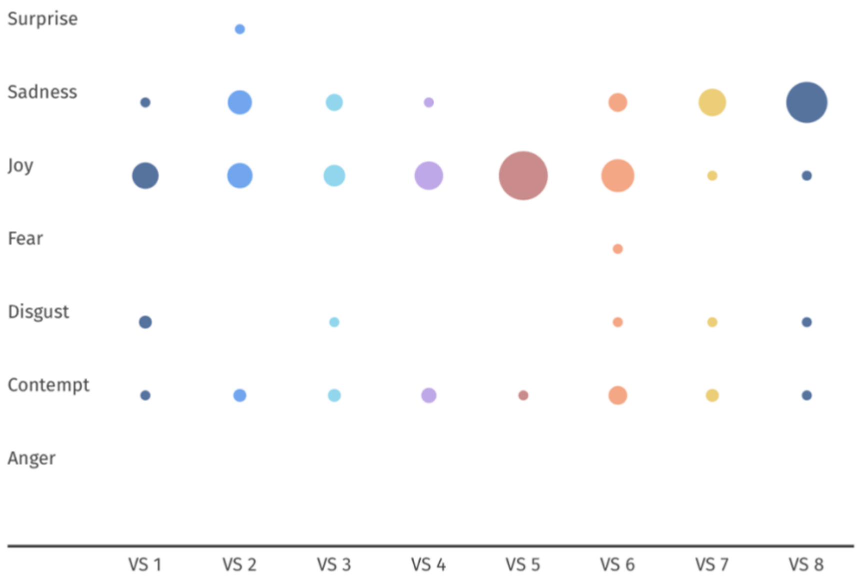


Figure 5. Time percentage for video stimuli for seven basic emotions of consumers based on Affectiva AFFDEX analysis
Source: Developed by the authors.

Joy was significantly greater in the VS5 group (42.41%), suggesting that it was particularly well received, while the VS7 and VS8 groups elicited minimal joy. Sadness showed substantial variation, with the highest response in VS8 (29.99%) and no response in VS5. Surprise was virtually absent across the videos, with a slight response in VS2 (0.83%). These findings reveal the varying emotional impacts of different video stimuli. VS5 stood out for having a very high percentage of joy, indicating that it was the most positively received. VS8 elicited the most sadness, showing a strong emotional impact in this regard. Both anger and fear were almost non-existent across all stimuli. Contempt varied across videos, with VS6 showing the highest response. Disgust and surprise responses were generally low, with few exceptions. Participants were more emotionally engaged with certain types of content, particularly those involving animations, which invoked more emotional engagement than other types.

The results of the Affectiva AFFDEX analysis, detailed in Table 9, show the percentage of time spent on neutral, positive, and negative emotions for video stimuli, as well as the engagement of consumers.

Table 9. Results of Affectiva AFFDEX analysis of the percentage of time spent on neutral, positive, and negative emotions and engagement of consumers with video stimuli

Type of the emotions	**Time Percentage for Video Stimuli**							
	VS 1	**VS 2**	**VS 3**	**VS 4**	**VS 5**	**VS 6**	**VS 7**	**VS 8**
Neutral valence	13.48	24.12	12.09	11.04	22.86	41.54	13.79	25.73
Positive valence	15.52	13.30	5.91	16.27	46.83	58.41	3.88	0.43
Negative valence	0.84	9.48	3.27	0.00	0.00	1.24	18.90	23.29
Engagement	103.34	96.54	98.50	97.04	87.10	93.91	95.78	93.47

Source: Developed by the authors.

Each video stimulus exhibited unique characteristics that influenced these emotional responses. VS1, characterized by positive emotions generated by AI with video and picture elements, showed 13.48% neutral, 15.52% positive, and 0.84% negative emotions, with a high engagement level of 103.34%. VS2, which was also positive and AI-generated with similar elements, had 24.12% neutral, 13.30% positive, and 9.48% negative emotions and an engagement level of 96.54%. VS3, featuring patriotism and positive emotions with human-generated text and video dubbing, had lower neutral (12.09%) and positive (5.91%) emotions but higher negative emotions (3.27%), with an engagement of 98.50%.

VS4, a humour-positive video with both AI and human-generated content, showed 11.04% neutral, 16.27% positive, and no negative emotions, with an engagement level of 97.04%. VS5, a positive emotion video without additional elements, had significant positive emotions (46.83%) but no negative emotions and an engagement level of 87.10%. VS6, with surprise-positive emotions and AI-generated content, showed high levels of both positive (58.41%) and neutral emotions (41.54%) with minimal negative emotions (1.24%) and an engagement level of 93.91%.

VS7, another surprise-positive video but with fewer elements, had 13.79% neutral, 3.88% positive, and 18.90% negative emotions and an engagement level of 95.78%. VS8, characterized by surprise-negative emotions and richness in elements, showed high neutral (25.73%) and negative (23.29%) emotions but low positive emotions (0.43%), with an engagement of 93.47%. These results highlight the complex relationship between the emotional content of videos and viewer engagement, demonstrating that videos with strong emotional contrasts, whether positive or negative, tend to elicit significant engagement and varied emotional responses.

5. Conclusions

This study explored cognitive and emotional responses to AI-related stimuli using GSR analysis and facial expression analysis. The data were collected from 24 respondents at Sumy State University, including students and researchers, and the stimuli were derived from AI-related videos focused on human development. The GSR data indicate that different stimuli significantly impact cognitive engagement levels. For instance, VS 1 elicited the highest average frequency of GSR peaks per minute (mean = 4.3664, SD = 2.6633), suggesting that it was particularly effective in maintaining participant attention and inducing consistent physiological responses. Similarly, VS 5 demonstrated significant cognitive engagement, characterized by both high frequency (mean = 4.2282, SD = 2.5063) and intensity of responses (mean average peak amplitude = 0.0486 µS). Other stimuli, such as VS 4 and VS 7, displayed a lower frequency but higher intensity of responses, indicating that while participants responded less often, their responses were notably strong when they did. For instance, VS 4 had a mean GSR peak per minute of 3.1055 (SD = 2.2071) and a mean average peak amplitude of 0.0453 µS (SD = 0.0677). VS 7 showed similar patterns, with a mean GSR peak per minute of 3.1573 (SD = 2.7783) and a mean average peak amplitude of 0.0483 µS (SD = 0.0818). These findings align with previous research suggesting that multimedia content can significantly influence cognitive and emotional engagement [84,85]. Additionally, theoretical frameworks such as cognitive load theory [86] suggest that the design and presentation of information significantly affect cognitive processing and engagement. The significant GSR responses to VS 1 and VS 5 support this theory, indicating that well-designed AI stimuli can effectively maintain attention and induce engagement. The emotional responses observed in the Affectiva AFFDEX analysis align with affective computing theory (Picard, 1997), which emphasizes the importance of designing technologies that can recognize and respond to human emotions. The Affectiva AFFDEX results revealed varying degrees of emotional engagement, with stimuli such as VS 5 eliciting high levels of joy (42.41%) and VS 8 eliciting significant sadness (29.99%). These findings highlight the complexity of emotional responses to AI-related content and the importance of considering both cognitive and emotional engagement when evaluating the effectiveness of AI interactions.

The Shapiro–Wilk and Levene's tests validated the use of ANOVA for comparing the means of the interaction types, confirming that the variances were homogeneous across the groups. This finding supports the reliability of the results and ensures that the observed differences in GSR peaks per minute were not due to random variability. Despite the differences in mean values among the stimuli, the ANOVA results indicated no significant association between GSR peaks per minute and the interaction types, as all p values were greater than the 10% significance threshold. This implies that, while individual stimuli showed significant effects, the overall pattern did not strongly differ among the types of interactions when all were considered together. Further analysis by gender showed that both male and female participants demonstrated similar high physiological responses to AI stimuli, with most stimuli eliciting statistically significant GSR peaks per minute for both genders. For example, for VS 1, females had a mean GSR peak per minute of 4.4588 (SD = 0.9983), and males had a mean of 4.12 (SD = 1.6303), both of which indicated significant engagement. This suggests that the type of interaction significantly impacts cognitive engagement across genders, although there are slight variations in response levels between males and females for specific stimuli.

The generalizability of the results is limited by the small sample size and the specific demographic composition of the participants, which included only students and researchers from Sumy State University. Future studies should consider a broader range of demographic variables, such as age, cultural background, and educational level, to determine how these factors may influence cognitive and emotional responses to AI stimuli. Additionally, incorporating a larger sample size and different AI-generated content types will help validate the findings and provide more comprehensive insights. Avenues for future research include exploring the long-term effects of repeated exposure to AI stimuli on cognitive and emotional engagement, examining the impact of interactive AI systems versus passive content, and investigating the role of context (e.g., educational vs. entertainment settings) in shaping user responses.

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