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Galvanic Skin Responses and Flow: Insights from Multimodal Learning Analytics in Personal Learning Environment

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Abstract: While digital learning offers advantages, it also presents challenges, including distractions from irrelevant websites. Such distractions characterize the personal learning environment (PLE), posing difficulties for learners and educators. Flow, an intrinsic motivation, is positively associated with learning outcomes, keeping learners engrossed and less influenced by external factors. Nevertheless, most prior research on flow has relied on surveys, and has overlooked the physiological aspect of flow during online learning. This study investigates the physiological signals of galvanic skin response (GSR) during flow experience in PLE. Using a natural online learning experiment, this study employed multimodal learning analytics to measure learners' cognitive processes objectively. The GSR, an indicator of cognitive load, was specifically used to measure and visualize physiological changes with different flow experiences in PLE. The results indicated that individuals with a high flow experience exhibited more stable emotional and stress responses than those with low flow tendency. This study is among the first to uncover the physiological shifts and stress reactions with flow experiences during the online learning process, offering a fresh perspective on flow theory via multimodal learning analytics.

Keywords: Leaning analytics, learning progress, physiological signal, flow experience

1. Introduction

Only by understanding the relationship between psychological phenomena and physiological responses can timely and accurate interventions provide support. The association between these two signals has been scientifically proven (Cacioppo & Tassinary, 1990). Physiological mechanisms such as heart rate, body temperature, and sweating produced by the autonomic nervous system are indeed closely related to emotions (Kreibig, 2010). Moreover, emotions influence human cognitive processes, affecting learners' learning experiences (Tyng, et al., 2017). Hence, learners would likely exhibit corresponding physiological signals during different learning and cognitive processes. However, there is still insufficient literature exploring physiological changes in learners during their learning process, especially within the PLEs.

This study utilized non-invasive galvanic skin response (GSR) sensors to measure learners' skin conductance changes during their natural experiment of online information search tasks. The developed scale confirmed learners' flow experiences during the experiment. Guided questioning and online information search tasks were used to simulate learners' learning within the personal learning environments, aiming to examine learners' flow tendencies and differences with their physiological signal responses.

2. Literature Review

2.1 Flow Experience

The theory of "Flow," also known as "Flow Experience" or "Optimal Experience," was established by Hungarian-American psychologist Csikszentmihalyi (Csikszentmihalyi, 2014). This experience is similar to a seamless and effortless state of mind, termed "Flow" (Nakamura & Csikszentmihalyi, 2001). Flow is considered as an intrinsic motivation. It's a dynamic system involving both the individual and the environment, and it's a subjective sensation (Csikszentmihalyi, 2014). In other words, each person only experiences flow when engaging in activities they find interesting and skilled in, and the balance of those factors is not the same for all individuals. The previous flow assessment predominantly relied on post-event interviews and questionnaires (Tian, 2017). However, as individuals were no longer in a state of Flow during these assessments, researchers started exploring the direction of physiological signals. This approach aims to understand the physiological changes that occur during the flow state, comprehending deeper into its effects on the body and allowing researchers to confirm whether participants experienced Flow during experiments more accurately.

2.2 Galvanic Skin Response (GSR) and Emotion

Galvanic Skin Response (GSR), a highly sensitive physiological indicator in psychology, has been used for about a century. Its principle is that when humans experience tension or stress, the sympathetic cholinergic nerves become active, stimulating sweat glands and leading to sweating in the hands, subsequently affecting skin conductance (Montagu & Coles, 1966). Therefore, GSR can be used not only as an indicator of stress but also to measure cognitive load (Nourbakhsh et al., 2012; Shi et al., 2017). In online learning environments, researchers found that inappropriate multimedia content might increase learners' extraneous cognitive load (Bian et al., 2016), especially within PLE that contains social media and irrelevant websites which lead to digital distraction (Wu, 2015).

2.3 The Multimodal Learning Analytics with GSR signals

Learning analytics studies mostly used behavioral logs to build predictive models. These models aimed to understand the relationship between the learning process and achievement outcomes, forming the basis for interventions and improvements in learning (Wu, 2021). However, learning is a dynamic processes involving diverse functioning. These processes are difficult to capture solely through a homogeneous data source (Liao & Wu, 2022). In recent years, educational researchers have attempted to analyze learners' physiological signals as a form of multimodal learning analytics to objectively understand learners' cognition and learning processes (Noroozi et al., 2019). Research employed Galvanic Skin Response (GSR) for multimodal learning analytics to understand cognitive load and stress during the learning process (Nourbakhsh et al., 2012; Larmuseau et al., 2020).

Past literature has shown GSR to be an effective indicator of learning arousal. Thus, this study employs multimodal learning analysis with GSR by examining learners' flow experiences in their PLEs objectively.

3. Methods

3.1 Natural Experimentation Design

This study aims to investigate the flow experiences of learners in their PLE, utilizing digital technology as a learning assistant tool. Therefore, the emphasis of the experimental design relies on creating appropriate contexts that induce learners to enter a state of flow while also collecting results through a Galvanic Skin Response (GSR) device. This research achieves this objective through guided tests involving information search and exploration.

3.1.1 Inquiry Guided Test Design

The test comprises two progressively challenging open-ended questions. The questions primarily delve into topics of a more specialized nature, requiring argumentation. This approach aims to trigger participants' autonomous online information search and engagement. Each question has a time limit of 15 minutes to allow participants to enter the online learning state. To answer them, participants must search for relevant information on the Internet, including blogs or social media.

3.1.2 Experimentation Process

Our institution's Institutional Review Board (IRB) completed this study's ethical review. Participants were initially given approximately 10 minutes to read and complete the informed consent form. They were then equipped with a Galvanic Skin Response (GSR) device. Afterward, participants were granted a 10-minute period of free activity, allowing them to use the laboratory's computer equipment as they pleased. This was done to simulate the scenario of digital learners frequently having unrelated websites open simultaneously (Wu & Xie, 2018).

Following this, participants engaged in a formal test session lasting about 30 minutes. Open-ended questions guided participants in autonomously searching for relevant information and organizing their findings. After completing the task, participants completed the Dispositional Flow Scale-2 (DFS-2; Jackson & Eklund, 2002).

3.2 Participants

This study recruited undergraduate and postgraduate students attending universities in the northern region of Taiwan through student Facebook groups. Interested individuals registered through a Google Form, and participants were randomly selected from the registrants. We recruited a total of 19 participants as valid samples in this study, including 9 males (47.4%) and 10 females (52.5%). Their academic levels ranged from sophomore to doctoral students, with a majority being third-year undergraduates (N=5) and second-year master's students (N=4). The participants' fields of study spanned 8 out of 18 academic disciplines, with engineering being the most common (N=8).

4. Instrument and Measurement

4.1 Shimmer Consensys and Kits

The physiological signals of participants were collected using a wearable Galvanic Skin Response (GSR) device (Shimmer Discovery in Motion, 2021). In the past two years, this device has been used in collaboration with 30 research institutions globally for experiments, and over 300 journal papers and conference proceedings have been employed, indicating a certain level of safety and harmlessness to the human body.

Consensys is the software that accompanies the Shimmer GSR sensor. It processes GSR data using specialized equations for signal processing, including signal collection, noise reduction, signal transformation, analysis, synthesis, filtering, evaluation, and identification (Shimmer Discovery in Motion, 2021). In this study we utilized the low-pass filter to extract the signals that below 0.5 Hz.

4.2 Dispositional Flow Scale-2 (DFS-2)

After completing the experiment, participants were asked to provide feedback on their learning experience during the experimental process by filling out the Flow State Scale (DFS-2), which was developed by Jackson & Eklund (2002). The complete scale consists of 36 items, encompassing 8 factors defined by Csikszentmihalyi as elements contributing to the experience of flow: Merging of Action and Awareness (MAA), Clear Goals (CG), Unambiguous Feedback (UF), Concentration on Task at Hand (CTH), Sense of Control (SC), Loss of Self-Consciousness (LSC), Time Transformation (TT), and Autotelic Experience (AE).

5. Result

5.1 Descriptive Statistical Analysis

The skewness and kurtosis fall within the mean of ±3, indicating a normal data distribution. Only the kurtosis of UF1 is slightly outside the acceptable range. The reliabilities of all factors demonstrate a high score consistency (All Cronbach αs ≥ .76). The composite scores are suitable for the follow-up statistical analysis.

5.2 Independent Sample t-test

The composite score of DFS-2 was used to indicate participants' flow tendencies during the information search experiment. Based on their scores, participants were divided into two groups: the high-flow group, consisting of the top 1/3 scorers, and the low-flow group, consisting of the bottom 1/3 scorers. Each group included 6 participants. The average flow score for the high-flow group was 4.39, while the average flow score for the low-flow group was 2.91. The results of the t-test analysis revealed a significant difference in flow scores between the two groups (t=8.13, p<.001).

5.3 GSR Waveforms with Different Flow Tendencies

This study further examined the waveform differences through graphical observation to gain a more specific understanding of the skin conductance changes in learners within PLEs. From the results depicted in the graph below, it can be observed that the high-flow group exhibited a stable, higher stressful state in terms of skin conductance. In contrast, the low-flow group displayed significant fluctuations in lower skin conductance throughout the experiment.

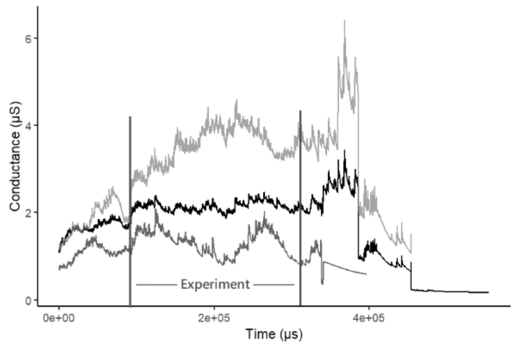

Figure 1. The GSR signals through a low-pass filter with varying flow tendencies through different filters. The grey line on the top represents the group of high flow tendency (M_{Flow}=4.39, N=6); the dark grey line on the bottom represents the group of low flow tendency (M_{Flow}=2.91, N=6); the black line in the middle represents the average of all the subjects (M_{Flow}=3.72, N=19).

6. Discussion

This study designed a natural experiment of online information searching to simulate learners' PLE scenarios. The study used the questionnaire and skin conductance response (GSR) measurements to assess participants' flow experience and physiological responses in a PLE. The findings revealed that the guided open-ended questions, which gradually increased complexity, effectively triggered students to experience flow. Additionally, the design of time-limited questions for 15 minutes each was a crucial factor in enhancing learners' focus (Wu & Xie, 2018). The t-test results indicated a significant difference in flow tendencies between two groups. the low-flow group displayed more significant fluctuations, suggesting that learners in the high-flow group were in a stable high-pressure state (Bakker et al., 2011).

According to Csikszentmihalyi's description of the flow experience (Csikszentmihalyi, 2014), it should evoke feelings of being immersed and effortless. However, study's GSR results showed that individuals with a high flow tendency were in a stable, high-pressure state. This objective physiological signal result seemed contradictory to the subjective experience, marking a significant breakthrough in the study of flow experience. In other words, even though the flow experience subjectively makes one feel relaxed and joyful, the physiological state during flow is characterized by a controlled state of heightened pressure.

7. Conclusion

GSR signals have proven effective tools for studying learning processes (Liu et al., 2022; Nourbakhsh et al., 2012). Therefore, this study designed a natural experiment coupled with wearable GSR signal devices to explore learners' flow experiences from a physiological perspective. The study innovatively visualized GSR data through time-domain waveform graphs, revealing that learners with a high flow tendency exhibited higher and more stable skin conductance. From this, it can be inferred that the flow experience involves a state of high concentration and pressure, even if subjective feelings of pressure are absent. This approach breaks away from traditional research centered around questionnaires and interviews. It confirms the physiological impact of flow experiences and demonstrates the interconnectedness of physiological stress and perceived concentration levels.

In the future, with the accumulation of a larger sample size and the application of more rigorous experimental manipulations and machine learning techniques. According to Csikszentmihalyi's theory, this approach would offer a more concrete perspective on flow and its physiological effects. Ultimately, this research could aid learners in more readily achieving flow experiences.

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