Synchrony Between Facial Expressions and Heart Rate Variability During Game-Based Learning: Insights from Cross-Wavelet Transformation

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Abstract. Game-based learning (GBL) environments are designed to foster emotional experiences conducive to learning; yet, there are mixed findings regarding their effectiveness. The inconsistent results may stem from challenges in measuring and modeling emotions as multi-dimensional constructs during GBL. Traditional approaches often use one data channel and conventional statistics to study emotions, which limit our understanding of the multi-componential interactions that underlie emotional states during GBL. In this study, we merged non-linear dynamical systems (NLDS) theory with the component process model of emotion to examine interactions and synchrony among two emotion signals during GBL, facial expressions and heart rate variability (HRV), and assessed its relation to knowledge and learning gain. Data were collected from 58 participants ($n = 58$) at a university in Central Finland while they learned about pathology with a tower defense game called Antidote COVID-19. Results showed a significant improvement in knowledge after GBL. A NLDS technique called cross-wavelet transformation showed there were varying degrees of synchrony between facial expressions and HRV. Neutral expressions showed the highest degree of synchrony with HRV, followed closely by happiness and anger with HRV. However, the synchrony between facial expressions and HRV did not affect knowledge and learning gain. This research contributes to the field by studying emotions as multidimensional systems during GLB.

Keywords: Emotions · Game-based Learning · Non-linear Dynamical Systems

1 Introduction

Emerging technologies present valuable opportunities to fulfill the United Nations Sustainable Development Goal 4 by promoting accessible, inclusive,

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and high-quality education [33]. Among these technologies, game-based learning (GBL) environments stand out by the game mechanics (e.g., aesthetics, narrative, incentive) designed to elicit engaging and emotionally-stimulating experiences conducive to learning [26]. Many studies find that GBL contributes to improved learning outcomes, more positive emotional states, and more motivation compared to typical educational approaches [3,9,23,26,35,46]. However, the benefits of GBL are not universal across learner groups [25,34,42], with studies indicating variability in GBL effectiveness based on factors such as gender and individual differences (e.g., prior knowledge) [18]. The variability in GBL's impact could possibly be explained by exploring multiple emotional processes that unfold during GBL to better understand their influence on learning.

Control-value theory (CVT) explains that emotions serve important functions during GBL, influencing motivational processes and cognitive resources (e.g., attention, memory, problem solving) [37]. Emotions arise from appraisals of external stimuli in the environment and internal processes such as prior knowledge [37]. In this way, an emotional state is multidimensional that results from a complex interplay among five components, including psychophysiological, behavioral, expressive, subjective, and cognitive [43]. Yet, typical approaches to studying emotions during GBL often rely on single-channel data analysis, which overlook their multidimensional nature. Accordingly, accurately and holistically measuring and modeling emotions might be crucial for advancing the field.

To address these challenges, we adopt an interdisciplinary lens to the study of emotions during GBL by merging non-linear dynamical systems theory with the component process model of emotion [43]. We employ a multimodal approach to study emotions as multi-dimensional systems during GBL, capturing the complex interplay among two emotional components–facial expressions and heart rate variability–to assess its role in knowledge and learning. Our hope is that by more comprehensively studying emotion, it will provide novel insights for developing more effective and emotionally-responsive GBL environments that cater to diverse learner needs, ultimately enhancing the impact of emerging technologies.

1.1 Literature Review

Emotions act as either a catalyst or a barrier to learning [7,26,37]. Many studies have examined relationships between emotions and learning with GBL environments. Common approaches study a single dimension of an emotion, typically via subjective data captured from surveys [23], or GBL interactions using log files [40]. While useful, unimodal data are limited in their ability to capture the five components that underlie an emotional state [43]. An emotional state emerges from continuously interacting components: psychophysiological, behavioral, expressive, subjective, and cognitive [43]. The component process model (CPM) [43] explains that when two or more of these components synchronize (e.g., psychophysiological and expressive), it leads to an emotional state. Yet, few studies have investigated emotional states based on the underlying interactions and coupling that may occur among multiple components during GBL.

By utilizing a multimodal approach that captures multiple emotion components, it could provide more insight into the degree of coupling among these components and possibly explain the mixed findings on the relations between emotions and GBL outcomes. Many studies have begun utilizing high-resolution devices to capture granular time series data on emotion processes, such as facial expressions via facial recognition software [4,34,46] or physiological signals, such as heart rate variability (HRV), electrodermal activity (EDA), and even brain activity [2,14,48]. HRV is particularly common in studying emotions because it is intricately linked to Polyvagal Theory [38] and is a non-invasive measure of the autonomic nervous system function. HRV represents the balance between the sympathetic nervous system (the "fight or flight" response) and the parasympathetic nervous system (the "rest and digest" response). Higher HRV is indicative of stronger vagal tone, suggesting that the body is capable of regulating arousal (e.g., stress) and returning to a state of equilibrium.

Using heart rate data, eye movements and brain waves, [48] studied emotions to assess their relation to learning. Emotions were operationalized based on changes in HRV, where fewer changes indicated a negative emotion and more changes indicated a positive emotion. The results showed a that the more positive emotions (via more changes in HRV) was associated with better learning outcomes. While there were no relations between the remaining data, it is important to note that there were some limitations in the analytical methods used that involved conventional statistics. This approach assumed that each of the signals were separate and independent of each other, missing any synchronization between channels during GBL to assess its relation to outcomes. Another study [17] used facial expressions of emotions, self-reported feelings, and EDA to measure emotions during immediate feedback on task performance. The results showed an increase in EDA following feedback on successful and failed tasks, and more positive feelings were reported after feedback on successful tasks. More negative emotions were reported after feedback on failed tasks, and there was a predominance of negative expressions after feedback on failed tasks compared to positive expressions. The findings suggest that multiple emotion signals may demonstrate similar patterns in relation to feedback on task performance. However, more questions remain about whether/how signals interact and couple during GBL and its affect on learning.

As discussed, conventional statistics are not designed to consider the interactions between multiple emotion components, yet they are the most commonly used to model emotional states [41]. Inferential models adhere to the central limit theorem [24], assuming that a whole is broken down into a sum of pieces, and the pieces are separate and independent of each others. While these models are very useful in many areas of research, they problematic when *solely* used to infer an emotional state. Interaction-dominant methods, such as those based in non-linear dynamical systems (NLDS), provide tools for mapping out the intricate dynamics and multi-layered interactions among the components that cause an emotion to emerge. [12,39]. A study [6] using interaction-dominant methods to examine multiple physiological signals, including EEG, Electrocardiogram (ECG), ElectroOculogram (EOG), EDA, Respiration, and facial electromyography (EMG) found that interactions among HRV and facial EMG predicted learning, compared to the other signals, possibly indicating an emotional state. The findings highlight that studying interactions among multiple emotion components could provide a holistic understanding of emotions and their influence on GBL outcomes.

1.2 Non-linear Dynamical Systems

Complex systems (CS) theory describes a complex system as a collection of interacting components that gives rise to complex behavior [30]. The components of the system interact over time, and through this interaction, emergent outcomes or states are produced at a meta-level. Non-linear dynamical systems (NLDS) is a branch of CS theory and provides techniques to examine how multiple system components change together and form emergent states. NLDA methods utilize relation- and time-intensive data to observe patterns of (ir)regularity across system components to understand how the system changes and adapts [16]. Recently, educational research has begun adopting NLDS equations to study comprehension [1], collaborative learning [31], and emotion mimicry [10]. [5] classified emotional states using a NLDS technique called recurrence quantification analysis (RQA). RQA examined how recurrent instances of facial expressions (via automated recognition software) co-occurred with instances of confused and frustrated behaviors (via interaction-based detectors trained using Baker Rodrigo Ocumpaugh Monitoring Protocol labels) [22,36]. Results showed that more learning gains were associated with more recurring facial expressions of sadness during confusion. In contrast, more prior knowledge was associated with more recurring disgusted facial expressions during frustrated behaviors, and less learning gain was associated with more recurring disgusted expressions during frustration. This research underscores the potential of NLDS tools to unravel the complex interplay of multiple emotional components.

1.3 Current Study

The objective of this paper is to study the role of synchrony among multiple emotion components–heart rate variability (HRV) and facial expressions–on GBL outcomes. We do so by adopting an interdisciplinary lens that merges CS theory [16] with the component process model (CPS) [43]. Our research questions are (1) Are there differences in knowledge assessment scores after GBL? We hypothesize there will be differences in knowledge after GBL, as suggested by prior findings [3,9,26]; (2) How do facial expressions and HRV synchronize during GBL? We hypothesize that facial expressions and heart rate variability will synchronize over time during GBL based on the characteristics of a complex system [16] and the CPM [43]; and (3) Are there relationships between facial expressions and HRV synchrony during GBL with knowledge (pre/post) and learning gains? We hypothesize that when facial expressions and HRV synchronize during GBL, it will be associated with learning gain and knowledge (pre/post); however, we do not provide the direction of this relationship since it may vary depending on the facial expression and HRV configuration (e.g., disgust+HRV vs. joy+HRV) [5,6,17,43,46].

2 Methods

Participants and Materials. A total of 81 participants completed this study but only 58 ($n = 58$) were included in our analysis due to issues, including 3 missing post-test data, 3 having low quality facial recordings, and 17 missing physiological data (due to hardware failures). Participants were recruited from a public university in Central Finland, and an ethics committee approved this study. Participants were compensated by partaking in a raffle for a chance to win a prize. The study lasted up to 2 h. Most participants reported that they were not first-generation college students (62%; $n = 36$), and more than half identified as Women (57%; $n = 33$), while 3% identified as Non-binary ($n = 2$), 38% as Men ($n = 22$), and 2% preferred not to say ($n = 1$). The average age was 26 years ($SD = 4.17$), and 14% indicated they played games regularly (at least once a week), while 8% said they played occasionally, and 3% said they never played games. However, 72% of the sample did not report game experience as this question was optional. Similarly, 12% indicated they were Asian, while 7% reported White/Caucasian, 5% Hispanic or Latino, and 3% Middle Eastern. Again, 72% of the sample did not report their race as this item was optional to report. Multiple validated instruments were administered before and after GBL to gauge emotions, gender identity, and motivation; but limited information is provided due to page limits. Knowledge assessments were created to capture knowledge of disease pathology and cellular biology. These assessments were created from the content in the GBL environment. Participants could complete the study in either English or Finnish.

2.1 Game-Based Learning Environment

We used a mobile or tablet game called Antidote COVID-19[1] in our study. Antidote was designed to increase knowledge about pathology through engaging gameplay. The game was developed by Psyon Games and endorsed by the World Health Organization[2] for its accurate content. The game introduces a narrative associated with the coronavirus that has infected a research team. The learner adopts the role of a scientist to develop a vaccine that combats COVID's spread. Learners can utilize resources and tools, including an encyclopedia to gather information on various cells, viruses, and vaccinations. Antidote is also a tower defense game, where learners apply their knowledge acquired from the encyclopedia. They must build cell walls to prevent pathogens from advancing to the stem cell (Fig. 1). Learners protect the cell's base using white blood cells (e.g., macrophages, monocytes) that engulf pathogens. As learners advance through the game, they unlock new white blood cells (i.e., more powerful towers) that enable the development of an increasingly effective vaccine.

1 https://psyongames.com/antidote-covid-19/.

2 https://www.who.int/news/item/19-10-2021-who-and-psyon-games-teach-players-how-to-stay-safe-from-covid-19-in-the-antidote-game.

Fig. 1. Example of tower defense with different white blood cells circled.

2.2 Procedure

Participants arrived at a laboratory during a scheduled appointment. A researcher greeted them and then participants provided informed consent before completing the pre-test. Next, participants were instrumented with a BioNomadix Wireless Photoplethysmogram (PPG) and electrodermal activity (EDA) Amplifier. Two electrodes were placed on the first two fingers of the non-dominant hand (to capture EDA). The PPG sensor was attached to the participant's ear to minimize noise from movements. Afterward, a researcher trained the participants on how to think-aloud during GBL; however, think-alouds were not analyzed in this paper. An example think-aloud was provided with the game, and once participants indicated they were ready, they were taken to an individual, sound-proof cabin with a desk. They played the game on an Apple iPad with an audio recorder on the desk. Video cameras were positioned above the desk to capture participants' faces. Participants were asked to follow specific instructions and complete 10 levels in the game within 1 hr. They were asked to verbalize their thoughts and feelings during GBL. After the hour, a researcher ended the recordings and game, and the participant was immediately administered the post-test. After, participants were asked to sit calmly for 1 min to capture their physiological baseline and then the study was complete.

2.3 Data Processing

Video, audio, and screen recordings and physiological data were synchronized using Noldus Observer XT[3] [Version 16]. FaceReader [Version 9.0] classified the intensity of facial expressions of emotions from video recordings of the face.

[3] https://www.noldus.com/observer-xt.

Heart-Rate Variability. Photoplethysmogram (PPG) was recorded at 2,000 Hz, which measures blood volume pulse via optical plethysmographic methods. This provides data to calculate heart rate and inter-beat intervals, including heart rate variability (HRV). PPG data were collected with BIOPAC Systems, Inc. and a wireless pulse transducer on the BioNomadix®[4] and MP160 Data Acquisition and Analysis system. Prior studies suggest that PPG data provide accurate interpulse intervals from which HRV measures can be derived (that are comparable to electrocardiogram data) [21,27]. AcqKnowledge® was used to extract inter-beat intervals (R-R) the provided a measure of the time difference between systolic peaks in heart beats. HRV indicates how much the heart's beat-to-beat intervals vary from one moment to the next. The R-R intervals were imported into Kubios HRV standard software [Version 4.1.0] and the root mean square of successive differences between normal heartbeats (RMSSD) were calculated. Noise artifacts were corrected using a cubic spline interpolation method [45]. This technique corrects for noise by comparing every RR interval value against a local average interval. Heartbeats that significantly diverged from the calculated norm were modified.

Facial Expressions. Videos of participants' faces were recorded during GBL at a sampling rate of 30 Hz and post-processed using FaceReader [Version 9.0] an automatic and validated facial recognition software. We obtained a paid license to access the full spectrum of post-processing features, including continuous calibration of individual faces. [44] found that FacReader achieved a 99% (average) accuracy classification rate for identifying facial expressions of emotions. The software works by using facial modeling techniques based on deep neural networks (DNNs) that identify 468 facial landmarks[5] and based on specific configurations of the landmarks, six basic emotions were classified. Basic emotions were defined using the Facial Action Coding System [8]. Additionally, the face finding algorithm is more robust to classifying facial expressions during talking, an advantage to studying facial expressions while collecting think-alouds [49].

A continuous calibration was used to account for individual differences in facial expressions. This calibration method continuously calculates the average expression using frames with the lowest model errors. Based on the highest model quality, these expression values are then calibrated to all future frames, creating threshold values that classify facial expressions. In this paper, we focused solely on facial expressions of anger, fear, contempt, joy, disgust, surprise, and sadness as prior studies have found associations between these facial expressions, learner-centered emotions, and learning outcomes [5,32]. We included neutral facial expressions in our analysis to serve as a comparison to the other facial expressions, and since they demonstrated the highest density during GBL (Fig. 2). Intensity scores were provided for each facial expression of emotion on a continuous scale from 0 to 1. The intensity scores were post-processed at 5 frames/second. FaceReader also provides metrics on model quality based on

[4] https://www.biopac.com/product/pulse-transducers-bionomadix/.
[5] https://www.noldus.com/facereader.

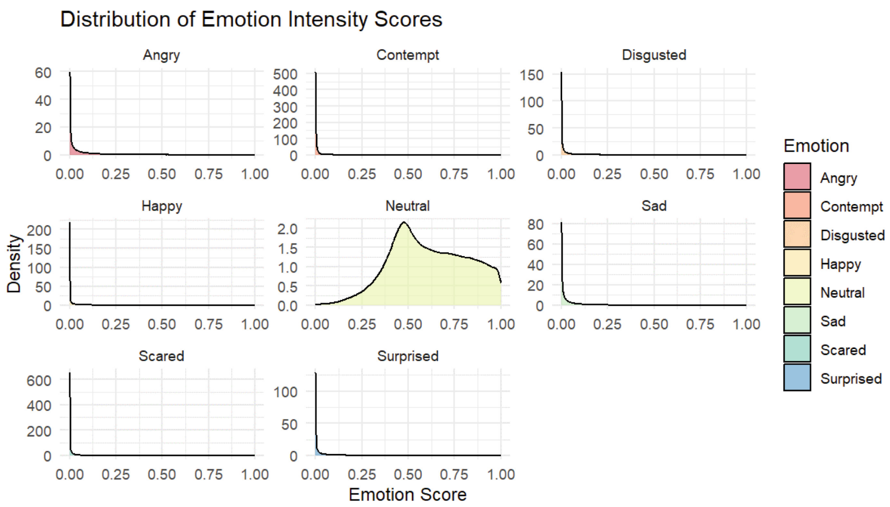

Fig. 2. Density plots of facial expression distributions.

the proportion of frames that could be analyzed at each frame. Instances of low model quality (<50% accuracy), or the researcher entered the participant's room to prompt a think-aloud, were removed. HRV and facial expressions data were aligned by averaging each modality at 1 s intervals.

Knowledge and Learning Gain. Knowledge assessments were developed using the content presented in the first 10 levels of the game, and it included 18 items: 4 open-response and 14 multiple-choice questions. To quantify the degree of learning gain, we used an equation that characterizes normalized gain based on score changes from pre- to post-test [28].

2.4 Cross-Wavelet Transformation

Cross-Wavelet Transformation (XWT) is a method for analyzing the time and frequency characteristics of two time series based on spectral decomposition. XWT focuses on how the power spectrum, which represents the strength of various frequency components, evolves over different component frequencies [19]. Points of significance describe the total number of times synchrony was achieved by two signals based on common amplitude [47] (Fig. 3). XWT has been used to study how learners coordinate movements during collaborative problem-solving [29] and conversations [11]. XWT metrics describe the degree of synchrony and the relative phase relationship between two signals. To obtain these metrics, we used the 'xwt' function from the biwavelet R package [13]. A Morlet mother wavelet was applied because it provides a good balance between time and frequency localization [15]. The following variables were extracted:

- **Average Common Power:** the common power or amplitude represents the degree of synchrony on a scale from 0 (no synchrony) to 1 (absolute synchrony), akin to how cross-correlation operates. We extracted and averaged

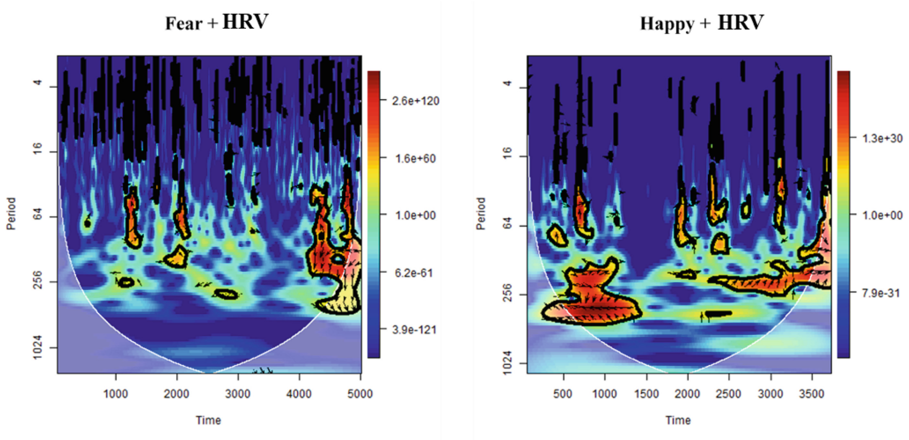

Fig. 3. Examples of XWT plots. Warmer colors indicate significant spikes in synchrony, while cooler colors show weaker correlation.

the common power within significant points ($p < .05$) across the component frequencies for each facial expression and HRV combination.
- **Total Points of Synchrony:** the total number of significant points ($p < .05$) across the component frequencies, suggesting the total number of synchronized moments across the different frequencies.
- **Average Relative Phase:** To describe the relationship between the signals, we estimated the mean phase difference. Relative phase reveals if the phases within a frequency are moving together (in-phase angle or 0°), in opposite directions (anti-phase angle or 180°), or leader-follow (between 0°–180°). A circular mean of the phase angle (over significant regions; recommended by [15]) was used via the 'circular' function in R [20].

3 Results

3.1 Preliminary Results

To control for the potential confounding influence of gender on GBL outcomes (suggested by [18]), we examined whether gender groups–women ($n = 33$), men ($n = 22$), non-binary ($n = 2$), and those that did not report ($n = 1$)– differed in knowledge and learning. However, since two of the groups (non-binary and did not report) were very small ($n < 5$), a Wilcoxon rank sum tests assessed differences in outcomes between men and women. Results showed no differences in pre-test scores ($W = 347.5$, $p = .7962$), post-test scores ($W = 364.5$, $p = .9862$), and learning gain between groups ($W = 405.5$, $p = .4704$).

3.2 Are There Differences in Knowledge Assessment Scores After GBL?

A Shapiro-Wilk normality test revealed post-test scores did not adhere to a normal distribution ($W = .95573$, $p = .03356$). A paired Wilcoxon Signed-Rank

Test found a significant difference in assessment scores from before (Med = 47.22) and after GBL (Med = 63.89), $V = 1$, $p < .0001$, $r = .13$). The results suggest that GBL had a significant (but small) effect on acquiring knowledge of microbiology. This finding supported our hypothesis where we expected there to be differences in knowledge before and after GBL [3,9,26].

3.3 How Do Facial Expressions and HRV Synchronize During GBL?

The XWT results indicated that neutral facial expressions and HRV demonstrated the highest average synchrony ($M = .37$; total points = 3668), demonstrating, on average, a moderate to strong level of synchrony during GBL. This was followed closely by anger and HRV ($M = .24$; total points = 3632) and happiness and HRV ($M = .20$; total points = 3646), compared to the remaining variables. In contrast, fear and HRV demonstrated the lowest average level of synchrony ($M = .04$; total points = 12; Table 1). Interestingly, the average circular degrees, which describe the differences in the phase relationships between the emotion signals, were 0 degrees. On average, the signals demonstrated in-phase relationships, where coupling occurred synchronously.

3.4 Are There Relationships Between Facial Expressions and HRV Synchrony During GBL with Knowledge and Learning Outcomes?

Multiple Spearman correlations were calculated with a Benjamini-Hochberg (B-H) correction to control a false discovery rate (FDR) due to multiple testing. The results showed a marginally significant and positive association between post-test knowledge scores and the average power between facial expressions of contempt and HRV ($r = .037$, $p = .0874$). However, after adjusting B-H FDR correction, the alpha was adjusted to a critical threshold of .0063 and the result was no longer considered marginally significant. Similarly, there was a marginally significant and negative association between learning gain and the average power between neutral facial expressions and HRV ($r = -.269$, $p = .0585$). However, after adjusting the critical threshold using B-H FDR (adjusted $\alpha = .0063$), the result was no longer marginally significant. There were no significant associations between variables of interest with pre-test, post-test scores, and learning gain ($ps > .05$). These findings did not support our hypothesis, where we expected relationships between the synchronization of facial expressions and HRV with knowledge (pre/post) and learning [5,6,17,43,46].

4 Discussion

This study explored how two emotional components–facial expressions and heart rate variability (HRV)–synchronize during game-based learning (GBL) and its relation to knowledge and learning. Our first research question (RQ1) revealed a significant increase in learners' knowledge after learning with Antidote COVID-19. This finding supported our initial hypothesis–that the GLB environment, Antidote COVID-19, would enhance knowledge, as supported by prior work

Table 1. XWT output between facial expressions of emotions and HRV.

Emotion Signals	Average Power	Total Points
Anger + HRV	.2351	3632
Contempt + HRV	.0394	12
Disgust + HRV	.1271	3626
Happy + HRV	.2034	3646
Neutral + HRV	.3679	3668
Sad + HRV	.1722	3638
Fear + HRV	.0745	3662
Surprised + HRV	.1518	3621

showing that GBL increases knowledge and benefits learning [3,9,26]. We found that learning outcomes were equal across gender groups, contradictory to [18] where there were differences in GBL outcomes between men and women. A possible explanation for differences could be explained by the domain of study. Antidote COVID-19 was designed on pathology content, while [18] focused on mathematics, a domain where gender differences are commonly reported.

To explore RQ2, a cross-wavelet transformation revealed the largest degree of synchronization existed between neutral facial expressions and HRV during GBL. This was followed closely by anger + HRV and happiness + HRV. Conversely, fearful facial expressions and HRV exhibited the lowest degree of synchronization during GBL. The analysis also showed there were in-phase relations across all facial expressions and HRV, supporting our second hypothesis, where emotional components interact and synchronize simultaneously, as supported by the CPM [43]. A possible explanation for the highest synchrony between neutral expressions and HRV could be due to several reasons. First, there was a large amount of neutral expressions in general during GBL compared to other emotional expressions, which were quite low (Fig. 3). This suggests that participants may be expressing neutral states if they are in a state of equilibrium or engaged with the GBL. Furthermore, more HRV indicates a stronger vagal tone, or a better balance between the autonomic and sympathetic nervous system. Thus, when more HRV synchronizes together with more neutral expressivity, then it may indicate that participants are actively engaged and focused on the content or task. Overall, the synchronization among expressive and HRV components, while small in some cases, suggests there may be repeated interactions over time that lead to component entrainment. This finding suggests that emotions behave as complex systems and requires further investigation.

RQ3 found no relationships between the degree of synchrony between facial expressions and HRV with knowledge and learning. This result did not support our hypothesis, where we expected associations between facial expressions and HRV synchrony with GBL outcomes, based on prior studies and CPM [5,6,17,43,46]. A possible explanation for the results could, again, be due to the low distribution of facial expression intensity (beyond neutral), possibly indicating there was a low intensity of facial expressions of emotions in general. Additionally, we collected a global measure of facial expressions and HRV, without focusing our analysis around interactions with different game elements designed to foster emotional engagement, an important assumption in CVT [37]. Collecting emotion components while learners read the encyclopedia vs. apply knowledge during game tasks could elicit different emotions based on different external events (e.g., demands, stimuli, etc.). Additionally, our study may yield different results based on different operational definitions and analysis, study design, domain, and procedures compared to prior work [6,17,46,48].

4.1 Limitations

Our study is limited by a lack of control group to compare emotions and GBL outcomes. Participants were also offered a prize, possibly creating bias via incentives. Additionally, facial recognition algorithms may hold bias since they are predominantly trained on white, male faces, possibly creating errors in the facial expression analysis. However, FaceReader has been empirically-validated with a high accuracy rate [44], and a continuous calibration was used to calibrate the algorithm to individual faces to account for individual differences in facial expressivity. Furthermore, we only included data in our analysis when the model quality demonstrated at least 50% accuracy. There are limitations to replicating this research since we used a paid FaceReader license to quantify emotions. There may also be limitations with utilizing ultra-short HRV measures.

4.2 Future Directions and Implications

We will examine the explanatory power of individual emotion components separately and together to determine whether individual and interactions among multiple components have more direct relations on accurately identifying an emotional state during GLB to assess its impact on learning outcomes. More data channels will be examined–facial expressions (extending to general facial muscle movements instead of specific emotions), HRV, and emote-alouds–during specific game interactions. This interdisciplinary and multimodal approach may provide a better understanding of the 1) variability of emotional states based on different configurations of multiple emotion components and their interactions during GBL, and its relation to learning outcomes, and 2) opportunities for building emotionally-responsive GBL environments that customize mechanics (e.g., content, scenarios) to specific emotional states that benefit GLB outcomes.

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