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Multimodal Analysis of Emotions in Gaming: Understanding Cultural Influences

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***Abstract*—This study investigates the emotional dynamics from different cultural backgrounds using a multimodal approach that combines Facial Emotion Recognition and Heart Rate Variability (HRV) analysis. A total of 109 participants from Italy, Japan, and Korea (mean age = 24.5 years) played two casual games, namely Snake and Matching Pairs, to investigate cultural differences in emotional and physiological responses. The results revealed distinct cultural patterns in static emotional expression using generalised linear mixed models (GLMMs). The Italian cultural group showed higher levels of positive facial expressions (FE), particularly happiness; the Korean cultural group showed more frequent negative FE, while the Japanese cultural group showed restrained FE, particularly related to fear. Moreover, emotional transitions were analysed using a Markov-inspired continuous-state operator derived from probabilistic FE vectors, which characterised the temporal structure of emotional changes and uncovered systematic cross-cultural and task-dependent differences in emotional latency. These findings show that emotional transitions are shaped by cultural norms and the cognitive demands of the games. Furthermore, integrating FE and HRV features into GLMMs showed that autonomic indices predict performance and vary across game types. Overall, this study provides three key contributions. First, it indicates that FEs of emotion during gameplay differ significantly across cultures, in accordance with cultural display norms. Second, it demonstrates that emotional transitions are dynamic and influenced by game performance, with cultural background shaping these patterns. Third, it identifies cross-cultural differences in physiological responses, specifically bodily signals such as HRV. These findings enhance understanding of how games elicit and regulate emotional and physiological responses, suggesting applications beyond entertainment.**

***Index Terms*—Video Game, Facial Emotion Recognition, Performance, Electrocardiogram, Markov Modelling, Generalized Linear Mixture Model**

I. Introduction

The study introduces an innovative multimodal approach that integrates Artificial Intelligence-based (AI), Facial Emotion Recognition (FER), and Autonomic Nervous System (ANS) response to investigate the profound effects of video games on human emotions. This research seeks to answer a fundamental question: *"How do video games influence individuals' emotional states across different cultural contexts?"* Over the past decade, video games have become a prevalent form of entertainment, widely consumed by billions of people worldwide across diverse demographics. Driven by rapid technological advancements, the video game industry has experienced significant growth, offering a variety of games that appeal to a broad audience [1], [2]. This global gaming community includes individuals of all ages and backgrounds, highlighting the substantial cultural and economic impact of video games [2]. Although emotional reactions in video games have been examined using and adapting various techniques, such as ANS measurements [3]–[5] and FER [6]–[9], most studies have been conducted within a single cultural context and rarely account for the sociocultural background of individuals. This limitation is consistent with findings from a recent systematic review on the cultural impact of video games, which highlights strong geographical biases, a predominance of qualitative approaches, and a limited consideration of how cultural background shapes players' interpretation and experience of game content [10]. Consequently, the role of culture in modulating emotional responses during gameplay remains largely unexplored, representing a significant gap in the current literature.

One of the most widely applied approaches to investigate emotions has been through facial expressions (FEs) [11], [12], and in recent decades, several models have been proposed [13], [14]. However, FEs can be voluntarily modulated and therefore may not always provide reliable indications of a person's emotional state. Peripheral physiological signals, such as the electrocardiogram (ECG) [15] and, in particular, its derivative metric, heart rate variability (HRV), offer complementary insights into ANS modulation of cardiovascular dynamics. The ANS constitutes a central bidirectional interface between brain, bodily states, and emotional processes, and emotional stimulation induces systematic adjustments in autonomic output via coordinated limbic and cortical pathways [16]. Although recent studies have shown that ANS responses do not map reliably or specifically onto discrete emotion categories [17]–[19], the heart rate dynamics can reflect broad dimensions of autonomic arousal and regulation. By integrating behavioural signals with HRV derived from ECG, our research aims to capture these dimensional autonomic changes during gameplay, rather than inferring discrete emotional categories. This combined behavioural and physiological approach advances our comprehension of the emotional impact of gaming. It provides a foundation for designing more immersive experiences and therapeutic applications, as well as for encouraging healthier gaming practices [20], [21].

In our methodological framework, we combined advanced AI-driven techniques along with biosystem modelling approaches. Specifically, we implemented a Machine Learning (ML)-based FER model, enhanced with Markov Chain (MC) modeling to interpret transitions between emotional states. Additionally, we extracted HRV metrics from ECG data to explore the dynamics of ANS in response to gaming stimuli [22]. Furthermore, Generalized Linear Mixed-Models (GLMMs) were fitted to assess the dominance of specific emotions and to determine whether cardiovascular dynamics could be altered

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by players' performance. A key methodological contribution of this study lies in its explicit cross-cultural structure. Rather than restricting the analysis to a single cultural setting, the present research investigates variations in emotional expressions and ANS responses across distinct cultural groups. This analysis of emotional reactions in gaming contexts could enable the design of more engaging and emotionally resonant games, offering crucial insights for developers and researchers aiming to optimize the user experience. Moreover, these insights will support the development of strategies to mitigate the emotional impact of gaming, ensuring that it remains a positive and healthy activity for the diverse range of players.

This study aims to explore the FE responses of players engaged in the two distinct video games, "Matching Pairs" and "Snake", employing a convolutional neural network (CNN). The focus is on analyzing FE and physiological signals, such as HRV, to unravel the multimodal dynamics of emotional reactions, emphasizing how different cognitive demands and game mechanics, such as performance, influence these responses. The literature has mainly focused on single cultural contexts; in contrast, the novelty of this study lies in its cross-cultural scope, comparing participants from Korea, Italy, and Japan cultural groups to reveal how cultural backgrounds shape emotional and physiological reactions during casual video games.

II. Related Studies and Study Framework

A. Related Studies

1) Artificial Intelligence, Facial Emotion Recognition and Emotions: In recent decades, AI has evolved from niche applications to an integral part of daily life, transforming human-machine interactions [23]. AI broadly refers to using computational power to mimic human cognitive abilities [24]. Its widespread adoption enhances efficiency across multiple domains, from autonomous vehicles navigating complex environments [25] to creative content generation [26], [27]. Correspondingly, FER has gained prominence in this domain, aiming to decode human emotions through facial analysis [28], [29]. Currently, complex CNNs dominate FER research, using the Facial Action Coding System (FACS) developed by Ekman to classify emotions based on facial muscle movements [30], [31]. FACS has proven instrumental in decoding seven core emotions (*angry, disgust, fear, happy, neutral, sad, and surprise*), making it a gold standard for FER applications [32].

FEs, which form the basis of FER, are widely regarded in the literature as communicators of emotional states, functioning as expressive and adaptive signals that bridge internal experiences with external social contexts [33]. Specifically, from the early stages of human development, expressions such as the social smile foster connections and secure caregiver bonds. In contrast, distress signals ensure survival by eliciting protective responses from others [34], [35]. Scholars from Charles Darwin to Paul Ekman have emphasized the evolutionary importance of these expressions in enhancing social cohesion and species fitness [34], [36]. Furthermore, Ekman's extensive cross-cultural studies have shown that while the basic patterns of FE are universally recognized, the intensity of these expressions is modulated by cultural norms [37], [38]. Many findings highlight the importance of cultural context in FER models, emphasizing the need to integrate diverse datasets to improve the technology's generalization and robustness. [37]

Although FEs have historically been treated as reliable indicators of internal emotional states, recent empirical research demonstrates that the relationship between *"facial movements"* and experienced emotions can neither be fixed nor exclusive. Facial movements refer to the patterned activations of individual or combined facial muscles, and these coordinated muscular actions collectively form what we recognize as FEs [39]. Large-scale reviews show that the same facial movement patterns, such as smiles, can emerge across a wide range of emotional and non-emotional contexts [39]. Moreover, Duran and Fernández-Dols showed that in their meta-analysis, the predicted configurations for so-called basic emotions co-occur with their corresponding emotional states far less consistently than previously assumed, suggesting that observable facial movements cannot be interpreted as one-to-one emotional readouts [40]. In addition, an experimental study with trained actors also demonstrates substantial variability in facial movements produced for the same emotion labels, supporting the idea that context strongly shapes how emotions are expressed and perceived [41]. Lastly, comparative studies using both human raters and automated classifiers show that neither can reliably infer felt emotions from facial movements alone [42]. Nevertheless, these convergent findings remain subject to debate in the literature, as FEs can sometimes align with emotional experience [30] and at other times diverge from it [39].

2) Arousal and Valence in Video Games: Video games can be analyzed across a broad spectrum, one of the most affected aspects is players' emotional activation. The diverse mechanics and high levels of immersion in video games uniquely influence players' emotional experiences. Players often experience a range of emotions, from *sad* and *happy* to *disgust* and *fear*, within a single gaming session [43]. These emotional responses are linked to the interactive nature of games, which require active participation in narratives and decision-making processes and to performance-related outcomes, where success or failure in the game can significantly impact a player's emotional state.

Various studies have examined the relationship between video games and emotions. For example, Przybylski et al. [44] found that video games that satisfy basic psychological needs, such as competence and autonomy, can increase players' positive emotions and overall well-being. Conversely, a study by Lemmens et al. [45] found that time spent playing violent games specifically increased physical aggression. They also found that excessive gaming could elicit more negative emotions. Furthermore, higher levels of pathological gaming (e.g., gaming addiction), regardless of violent content, predicted increased physical aggression in boys. Nevertheless, these studies, and many others in the literature, focus primarily on psychological aspects, relying on self-report measures rather than integrating physiological or behavioral data to understand the emotional impact of video games on individuals.

The interplay among psychological and physiological variables and contextual elements, such as environmental factors and specific stimuli, is crucial in shaping emotional arousal and valence. In the context of video games, these dimensions serve as key descriptors of players' emotional states, based on the circumplex model of emotion [46]. Arousal reflects the degree of emotional intensity or activation, spanning a spectrum from low to high [47]. Studies indicate that video games of different genres variably influence arousal levels, underscoring the importance of both the game's genre and its mechanics, including aspects like scoring systems, time constraints, and platform type [48]–[50]. Valence, on the other hand, characterizes the positive or negative quality of an emotional experience, influencing not only player performance but also their overall engagement with the game [51]–[54].

These emotional dimensions are closely linked to physiological responses during gameplay. For example, Calà et al. showed that casual video games can increase positive emotions while reducing negative ones, with correlations between arousal and the Largest Lyapunov Exponent (LLE), and between negative emotions and pupil diameter variability [55]. Similarly, Hazlett used electromyography (EMG) to identify negative emotional reactions during high-intensity gameplay, even when cognitive load could act as a confounding factor [56]. Moreover, video games are a strong medium for eliciting complex emotional responses and are widely used in the literature [57]–[59]. Overall, these findings suggest that different video game genres may produce distinct physiological effects.

3) HRV as Index of ANS and Psychophysiological Regulation: HRV reflects the fluctuation in time intervals between consecutive heartbeats, typically measured as RR intervals in the ECG, and is a key physiological marker of ANS function. It captures the dynamic interplay between sympathetic and parasympathetic modulation of cardiac activity, with higher HRV generally associated with better cardiovascular health and more adaptive autonomic regulation [60], [61]. Conversely, reduced HRV is linked to pathological conditions such as cardiovascular disease, stress, and autonomic dysfunction [62]. The physiological interpretation of HRV has been progressively refined through psychophysiological research, particularly with respect to its frequency-domain components. High-frequency (HF) HRV is widely accepted as a selective marker of cardiac parasympathetic (vagal) activity due to its strong coupling with respiratory rhythms, whereas low-frequency (LF) HRV reflects a combined contribution of both sympathetic and parasympathetic influences rather than pure sympathetic tone [63]. In recent years, the relationship between HRV and emotional or cognitive states has been extensively documented. Particularly, higher HF-HRV is typically indicative of stronger parasympathetic influence, while emotionally arousing or cognitively demanding conditions are associated with reductions in HF-HRV, reflecting increased sympathetic activation and vagal withdrawal. Accordingly, HRV metrics, particularly frequency-domain indices, have been validated as reliable markers of psychophysiological stress and emotional engagement [64], [65]. For instance, challenging cognitive tasks or emotionally stressful events can induce a shift in HRV spectral power from HF to LF components, indicative of heightened arousal and increased sympathetic dominance [65]. Beyond time- and frequency-domain indices, nonlinear HRV features provide enhanced sensitivity for characterizing psychophysiological states. Methods such as Recurrence Quantification Analysis (RQA) [66] capture dynamical properties of cardiac regulation that are not accessible through linear metrics alone. Evidence indicates that RQA-derived measures can discriminate levels of cognitive engagement and physical stress over short time windows and may perform comparably or better than traditional HRV measures when assessing interpersonal synchrony and autonomic adaptation [66].

B. Study Framework

In this study the *Step Ia* provides a broad, static overview by examining overall distributions of FEs across cultures. This step recognizes general patterns of FE, establishing how different cultures outwardly experience FE during gameplay. Building on this, *Step Ib* strengthens the dynamic analysis by focusing on and evaluating core FE patterns across different contexts. This strategy helps for a more comprehensive understanding of cross-cultural differences before introducing temporal dynamics. Consequently, *Steps I and Ib* together form an integrated approach that characterises the static and dynamic structure of FE. Lastly, *Step II* focuses on the underlying mechanisms by analyzing physiological signals, particularly HRV, to reveal how physiological processes accompany and regulate both expressions and their temporal dynamics. Through this progression from static analysis of FEs to dynamic changes, and finally to physiological responses, the outcomes establish a coherent path from general patterns toward more specific mechanisms.

1) Step Ia: Static Distribution of Facial Expressions Across Cultures: Various studies in the literature highlight the significant influence of culture on emotional experience and expression [37], [38], [67]. For instance, individuals in Italian cultural contexts, shaped by historical and sociocultural developments, may place a relatively stronger emphasis on pleasure-oriented values, reflecting a more hedonic lifestyle compared to some other cultural contexts [68]. Such cultural orientations may also be reflected in leisure-related motivations, including those associated with video gaming. In a study by Gursesli et al., ”entertainment” emerged as one of 12 distinct motivational clusters and was particularly endorsed by Italian gamers [69]. This finding suggests that cultural differences may shape everyday preferences and engagement in casual activities, leading to the first research hypothesis:

Hypothesis 1.1 (H1.1). Italian cultural group is expected to exhibit a higher probability of happy FE and a lower level of negative FE compared to Japanese and Korean cultural groups while playing Snake and Matching Pairs games.

Asian cultural contexts, including gaming-related environments, have been described in the literature as placing a relatively stronger emphasis on competitiveness, which can be associated with a higher likelihood of negative emotional displays in some settings [70], [71]. Negative emotions can generally be divided into two major categories: action-oriented and inhibition-oriented. Action-oriented emotions, such as *angry* and *disgust*, typically motivate individuals to engage in approach-related behaviours. Conversely, inhibition-oriented emotions, such as *fear* and *sad*, are more likely to be linked to passive or avoidant responses, potentially resulting in reduced perceived control or disempowerment. In the case of Japan, for example, the expression of certain negative emotions (e.g., *fear*) has been reported to be more restrained, consistent with collectivistic cultural orientations and implicit norms governing emotional display rules [72], [73].

Whereas individualistic cultural contexts (often discussed in Western settings) frequently emphasize authenticity in emotional expression, collectivistic cultural contexts place greater emphasis on adapting one’s behaviour to the social situation in order to avoid interpersonal impropriety. Emotion regulation and “masking” behaviours have been reported to be particularly salient in Japanese contexts [74], where individuals are often observed to suppress expressions of *fear*, especially in the presence of authority figures such as an experimenter [75]. Furthermore, qualities such as fearlessness, integrity, and bravery have long been valued in Japanese philosophical and cultural traditions, including Bushido, Shintoism, Confucianism, and Buddhism [76]. Although these ideologies do not directly dictate the suppression of *fear* [77], they have contributed to social norms and implicit emotional display rules that can influence such behaviour and may serve as moderating factors. In addition, some studies have described competitiveness-related norms in Japanese cultural contexts, which have been linked to negative emotional experiences in certain settings [78], [79]. Considering this literature, we therefore hypothesize that:

Hypothesis 1.2 (H1.2). Japanese cultural group is expected to be less likely to show fear FE compared to Italian and Korean cultural groups while playing Snake and Matching Pairs games.

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Existing research suggests that individuals from Korean cultural contexts may exhibit more frequent expressions of negative emotions, both verbally and non-verbally, in response to various social and personal triggers. Studies by M. Kim [80], [81] and Y. Kim [82] have revealed that emotions such as *sad, angry, disgust*, and shame are frequently experienced, especially in situations involving personal failure [83]. This pattern may reflect culturally shaped norms related to competitiveness reported in prior research, such as achievement-related expectations and performance pressure, which may be more salient for some individuals within this cultural context [84]. In this sense, academic, career, or social competition can lead to frustration and increased sensitivity to failure or perceived incompetence. Moreover, several studies show that this competitive cultural structure is also effective on video game players [85]. In addition, literature highlights that competitive behaviours are related to negative emotions [86], [87]. Taking these studies into account, we thus propose that:

Hypothesis 1.3 (H1.3). Korean cultural group is expected to be more likely to show negative FE compared to Italian and Japanese cultural groups while playing Snake and Matching Pairs games.

Overall, in this step, the focus on *happy* and *fear* in *H1.1 and H1.2* are grounded in culture-specific findings. Italian cultural psychology research [68] highlights a strong hedonic orientation, making *happy* a particularly relevant emotion for examining expressive tendencies among the Italian cultural group. In contrast, Japanese cultural groups consistently report that *fear* is the emotion most likely to be suppressed due to collectivistic norms and sensitivity to social hierarchy. For Korean cultural group, previous research does not emphasize one specific emotion. Instead, the literature describes a broader pattern of competitiveness-related negativity that spans *multiple negative FEs*. For this reason, *H1.3* was formulated at the level of overall negative valence rather than at the level of a single discrete emotion. However, we note that such culturally framed expectations should not be taken as essentialist claims about the groups, but as probabilistic tendencies motivated by previous studies.

2) Step Ib: Dynamic Transitions of Facial Expressions Across Cultures: People's emotional state dynamics are essential in the context of video gaming. Video games, especially when offering high cognitive content, elicit rapid changes in the subject's emotional state, which, on a social and nonverbal level, are mainly expressed through changes in facial features [34], [36]. This dynamic structure, while emerging from distinct facial patterns associated with different emotions, should also be considered in light of one of the most critical metrics influencing affective responses, i.e., cognitive load. Although emotional responses span a wide spectrum, they are highly sensitive to variations in cognitive demands, which can rapidly modulate how individuals experience and express affect. The literature has shown that affective states are not merely a reaction to external stimuli and cognitive activities. For instance, studies investigating performance in complex cognitive tasks such as goal attainment [88], school exams [89], or competitive sport [90] activities have shown that success or failure in task execution directly shapes participants' emotional states. High cognitive load often leads to negative emotions such as sadness, whereas successful performance under demanding conditions is typically associated with positive emotions such as happiness.

These results highlight that cognitive processes and emotional states are crucial for understanding how emotions evolve and change during dynamic events such as video games. Specifically, the link between emotions and cognitive load in video game contexts has been investigated in several studies [91], [92]. According to Yeh et al. [93], an analysis considering the complex time-varying dynamics of emotional states was also implemented. Moreover, the main research question was how different types of video games affect players' FE, as the Snake game is mainly based on reactivity and speed. In contrast, the Matching Pairs game involves more mnemonic and attentive processes.

Accordingly, we initially employed a self-reported questionnaire to assess participants' emotional states. To this end, a preliminary analysis was conducted on participants' game performance and their scores on the Positive and Negative Affect Schedule (PANAS) questionnaire. However, self-report questionnaires are subject to self-report biases, such as participants' tendency to provide socially desirable answers (e.g., honesty bias) and their limited ability to accurately assess their own emotional states (e.g., introspective ability) [94], [95]. Furthermore, these tools are limited to capturing emotions at two fixed points (before and after the experience) and are not well-suited to analyzing the dynamic, instantaneous changes in emotional states during gameplay. To overcome these limitations and gain a more continuous understanding of emotional dynamics during gameplay, we used a Markov Chain (MC) -inspired approach [96] to model transitions between different emotional states over time.

This approach allows for the investigation of emotional transitions in subjects looking for time-variant emotional patterns that can identify differences in the different populations, both in the cultural context and game performance. *Step Ib* aims to investigate how FE dynamics evolve in response to game-related stimuli and how these patterns vary across cultural, cognitive, and contextual factors. Specifically, the analysis focuses on identifying whether participants from *different cultural backgrounds* exhibit distinct temporal patterns in their FEs, exploring also how individual differences in *task performance* relate to variations in these dynamics, and examining the extent to which the *type of game* shapes the temporal structure of emotional transitions.

3) Step II: Multimodal Integration of FE and HRV Data to Model Gameplay Performance: This step investigated ANS changes during gameplay and their relationship with FEs and cultural background. The focus was on acquiring ECG signals [97], which were used only to extract HRV, the time-interval variation between consecutive heartbeats. It is widely recognized as a way to assess ANS behaviour in terms of sympathetic and vagal branch functions, both in normal and pathological conditions [98]. The HRV has also found applications in video game studies, helping researchers assess players' stress levels, emotional responses, and engagement [99] while providing valuable data for adaptive game design [100] and therapeutic interventions [101], [102]. Recently, these findings have led researchers to design biofeedback-based games that use HRV features to manage stress and maintain optimal arousal levels, thereby improving gameplay experiences and mental well-being [103]–[105]. The integration of HRV data allows for Dynamic Difficulty Adjustment [106], [107], enabling games to adapt in real-time to players' physiological states, ensuring a balanced challenge that keeps them engaged without being overwhelm. However, HRV analysis in different cultures, in the video games context, is limited to bio-feedback applications and is not considered for exploring the underlying cognitive processes during games. Finally, *Step II* aims to examine how *ANS activity*, as captured by *HRV*, interacts with *FE patterns* to shape players' behavioural responses during gameplay across cultures. The analysis focuses on determining whether multimodal physiological and emotional signals offer complementary insights into task performance, exploring how HRV-based indices of autonomic regulation relate to variations

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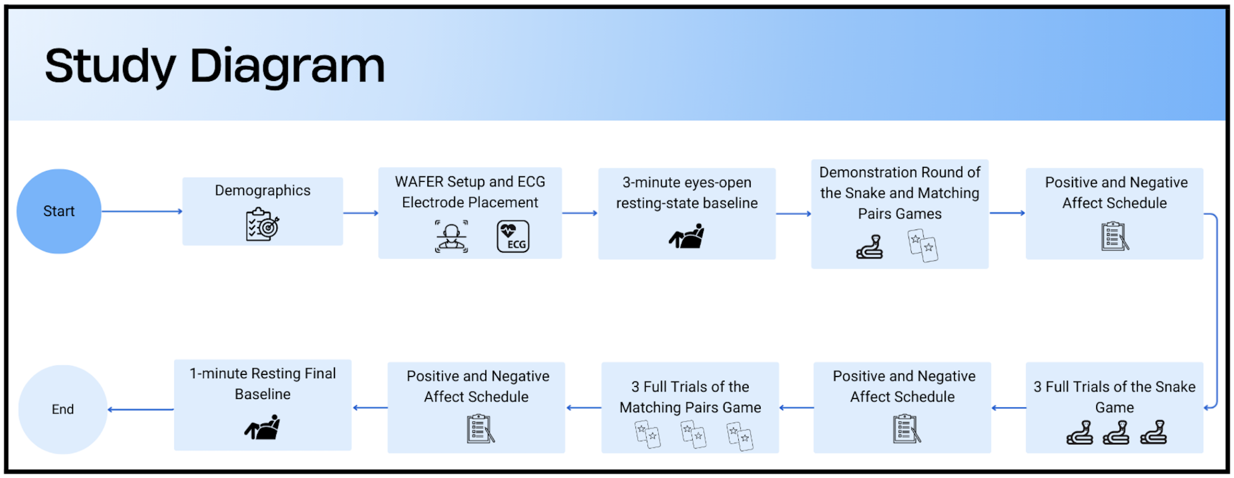

Fig. 1: Overview of the Study

in emotional expression across the session, and assessing whether these relationships differ by game type and players' cultural background.

III. Materials and Methods

A. Materials

1) Participants and Experimental Procedure: A total of 109 healthy volunteers from three different cultures participated in the study, comprising 30 Italian culture (mean age = 26.1 years, 13 females, 15 males, 2 non-specified), 40 Korean culture (mean age = 24.375 years, 9 females, 30 males, 1 non-specified), and 39 Japanese culture (mean age = 23.38 years, 3 females, 35 males, 1 agender). The overall mean age of participants was 24.5 ± 3.5 years. The study received approval from the Institutional Review Board (endorsement of compliance with the Opinion of the Ethics Committee for Research no. 275 of 04/09/2023), and all participants provided written informed consent. The study also adhered to data protection regulations, including the Act on the Protection of Personal Information (APPI) in Japan, the Personal Information Protection Act (PIPA) in South Korea, and Law Decree DL-101/2018 in Italy. Participants were seated approximately 50 cm from a monitor and engaged in the video games. For the *Snake* game, they used the arrow keys (the *up*, *down*, *left*, and *right*) on the keyboard to navigate, while the *Matching Pairs* game required the use of a mouse and its left button to select pairs. Before beginning the experimental session, participants engage in a demonstration of each video game to become acquainted with the tasks. These demo rounds are not factored into the performance evaluation. During the experimental session, participants complete three consecutive trials of the Snake game followed by three consecutive trials of the Matching Pairs game. Figure 1 shows a complete overview of the experimental procedure.

The experiment followed a detailed operational protocol that specified standardized procedures for the conduct of the study, and all sessions took place in a laboratory-controlled environment. To maintain consistent visual and physiological recording conditions, ambient lighting was controlled by darkening the windows and keeping the ceiling lights continuously on throughout data collection. Participants were seated in an adjustable chair that was set to a fixed height, and their distance from the webcam was standardised using a marked position on the table to minimise variation in posture and upper-body orientation. They were instructed to maintain an upright seated position, keep their feet flat on the floor, and refrain from unnecessary body movements during the recording period. These measures were implemented to reduce variability in the physiological signal that might arise from differences in posture or gross bodily movement.

2) Positive and Negative Affect Schedule: The Positive and Negative Affect Schedule (PANAS) was used to assess participants' emotional states. Originally developed by Watson et al. in 1988 [108], PANAS is a self-report scale structured in a five-point Likert format. It comprises 20 items, split into 10 measuring positive affect and 10 measuring negative affect. Watson et al. demonstrated that PANAS is both reliable and valid, reporting Cronbach's alpha values between 0.86 and 0.90 [108]. In this study, the Italian version of PANAS, validated by Terraciano et al., was administered to Italian participants [109]. This version of the scale demonstrated an internal reliability coefficient of $\alpha = 0.76$ [109]. For the Korean cultural group, a modified PANAS version was used, differing from the original by including 11 negative and 9 positive items. According to Lee et al., this adjustment was made because the word "Alert" carries a negative connotation in Korean [110]. This version demonstrated reliability scores of 0.88 for positive affect and 0.87 for negative affect [110]. Finally, the Japanese version of PANAS, validated by Kawahito et al., was employed for the Japanese cultural group [111]. This adaptation retained the original structure of 10 positive and 10 negative items, with reliability coefficients of 0.87 for positive affect and 0.88 for negative affect [111]. Thus, for PANAS-related analyses mean scores were used instead of summed scores to account for these differences in the administered PANAS versions.

3) Web-Agile Facial Emotion Recognition (WAFER): The Web-Agile Facial Emotion Recognition (WAFER) platform represents a real-time, web-based system that integrates AI models for FER. The Custom Lightweight CNN-based Model (CLCM) is central to WAFER's functionality and is an explicitly optimized CNN for FER tasks [112], [113]. This model builds upon the MobileNetV2 architecture [114], employing a transfer learning approach to enhance its performance by replacing the final layer with a tailored classifier, thus refining its capacity to detect and classify emotional expressions [115].

For this study, the CLCM model was trained using the Real-world Affective Faces Database (RAF-DB), a comprehensive multinational dataset recognised for its diverse representation of facial expressions [116], [117]. RAF-DB provides a 7-dimensional expression distribution vector for each image, along with detailed annotations including accurate and automatic landmark locations (5 and 37 points), bounding box information, and demographic attributes such as race, age range,

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and gender. Consistent with standard practice, we used the official training and test split, retaining the test set exclusively for final model evaluation. No dataset balancing techniques were applied, thereby preserving the natural distribution of the seven basic emotions reported in the original RAF-DB study [117]. Following the methodological approach of the original CLCM study [115], the model was trained directly on the seven-emotion subset. All images were converted to grayscale, resized to 224×224 pixels, normalised, and augmented with light transformations such as horizontal flips, zooming, shearing, and shifts. Using 20% of the training split for validation, the model was trained for 100 epochs with a batch size of 64, a learning rate of 0.0001, and the Adam optimizer. Under these conditions, the CLCM model achieved 84% accuracy on the RAF-DB test set [115].

WAFER's analytical framework aligns with Ekman's theoretical constructs of seven primary facial expressions (*angry, disgust, fear, happy, neutral, sad, and surprise*) delivering results as cumulative percentages that collectively sum to 100% [30], [34], as these values are continuous for each emotion category. WAFER outcomes are provided at a sampling frequency of *1 Hz* during the experimental sessions, enabling continuous emotion classification. This high-frequency data acquisition enables detailed analysis of dynamic emotional shifts, offering valuable insights into transient emotional states in response to stimuli encountered in interactive and immersive environments.

4) Snake Game: The Snake game implemented in this study closely resembles the traditional version (Fig. 2) and has the primary objective of consuming as many items as possible. Unlike some variants, this version of the Snake game does not implement a countdown timer. Instead, gameplay concludes when the snake's head makes perpendicular contact with either its own body or the boundaries of the playing area. Before the real experiment, each participant played a demo game to familiarize themselves with the game commands. The demo round does not count towards the final score. A dedicated scoring system for the Snake game has been designed to reward both efficiency and precision, adjusting for the increasing difficulty as the snake lengthens during gameplay. The game performance score (S_{GP}) is calculated using the snake's initial pixel length ($L_0 = 5$) and the playing area in pixels ($PA = 400$), factoring in the number of items consumed (EI), as expressed in Equation 1:

$$S_{GP} = \begin{cases} \sum_{k=1}^{EI} \left[(1 + \frac{k}{L_0}) - \frac{\Delta T_k}{PA} \right], & k > 0, \\ 0, & k = 0, \end{cases} \quad (1)$$

where ΔT_k is the time taken to consume each item.

The equation 1 reflects a balanced approach to scoring, emphasizing the player's ability to consume items efficiently and the adaptive challenge posed by the snake's increasing length.

5) Matching Pairs Game: The Matching Pairs (Fig. 3) game implemented in this research is a modified version of the standard format. It includes six symbol pairs, totalling twelve symbols. The game begins with a 35-second countdown, after which the participant starts playing. The game ends in two ways: either the countdown runs out, or the participant successfully matches all pairs of symbols. The symbols used in the game are designed to be easily distinguishable by shape and colour, which helps to reduce confusion and increase attention. Each participant plays three rounds of the game during the actual experiment. Before the real experiment, each participant plays a demo game to familiarize themselves with the game commands. The demo round does not count towards

Fig. 2: Illustration of the Snake game, during gameplay and upon completion.

the final score. The position of the symbols is randomized after each round of the game to ensure variability and maintain the game's challenge.

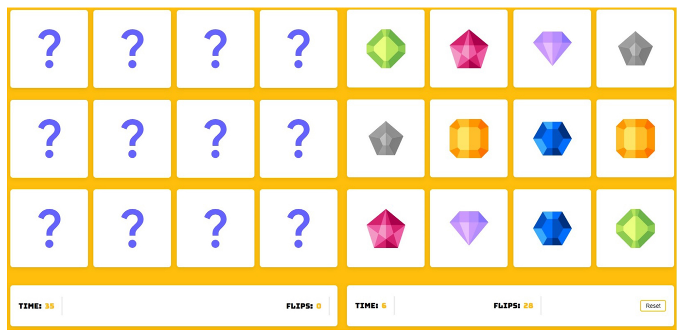

Fig. 3: Illustration of the Matching Pairs game, before start and completed.

The scoring algorithm for the Matching Pairs game is designed to reward accuracy and speed. *Successes* account for 3 points, while *fails* assign 1 point penalty to the player. Additionally, the algorithm implements a bonus (or a penalty) system for streak matches of *successes* (or *fails*). Finally, the game rewards players for finishing the game faster. A constant reward is given for completing the game in under 35 seconds, with additional points awarded based on how much faster the completion is relative to this threshold. If the participant does not finish the game in 35 seconds, he does not receive the reward. The details of the scoring algorithm and equations for the Matching Pairs game are shown below:

- the Matching Pairs game performance score (MP_{GP}) is calculated by summing the base score, streak bonuses, and the time bonus in Eq. 2:

$$MP_{GP} = 3 \times successes - fails + \sum SB_i + TB \quad (2)$$

- the streak bonus for the *i*-th streak (SB_i) is calculated using Eq. 3:

$$SB_i = \sum [1 + a \times (s - 1)] \quad (3)$$

where a is 0.5 for positive streaks (*successes*) and 0.75 for negative streaks (*fails*); s represents the number of matches in the streak after the first one;

- the time bonus (TB) is awarded based on the total completion time T, and calculated with Eq. 4.

$$TB = b \times (35 - T) \quad (4)$$

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where T represents the finishing time of the Matching Pairs game, b is a factor that depends from T: $b = 0.5$ for $T < 20s$, $b = 0.3$ for $20s < T < 30s$, $b = 0.1$ for $T > 30s$ and $b = 0$ (*i.e.* no TB) for $T = 35s$.

According to their performance, players were then categorized as either *high-scoring* or *low-scoring* for each game. Specifically, this classification was based on the median game performance (GP) scores of the population, enabling the distinction between participants with higher and lower task proficiency and the investigation of how skill level modulates emotional and cognitive responses during gameplay. The scoring analysis identified 54 *high-scoring* and 55 *low-scoring* individuals for the Snake game ($median = 12.69$, $mad = 18.14$, $max = 141.11$, $min = 0$), and similarly, 54 *high-scoring* and 55 *low-scoring* individuals for the Matching Pairs game ($median = 28.6$, $mad = 7.39$, $max = 41.83$, $min = -17.98$).

B. Methods

This section outlines the methodological framework of the study, which integrates a multimodal set of tools to examine emotional and physiological responses during gameplay. In this study, specifically in *Step Ia* and in *Step II*, we implemented a GLMM approach, as it represented the most appropriate framework for our data structure. Unlike repeated-measures ANOVA, which requires normally distributed residuals and equally spaced observations, GLMMs flexibly accommodate repeated measures and non-normal outcomes, such as skewed facial-expression activations and game performance scores. Similarly, although Generalized Estimating Equations (GEE) handle correlated data, they estimate only population-level effects and do not allow subject-specific random effects, which are essential in our design given the large variability in emotional and physiological responses across participants. Specifically, in *Step Ia*, the primary goal was to compare facial expression activations across cultures and game types, whereas *Step II* focuses on predicting game performance from facial expression and HRV features.

Moreover, in *Step Ib* we complemented the GLMM analysis of *Step Ia* with a MC-inspired approach to capture the within-session temporal dynamics of FE states. Although GLMMs are well-suited for estimating trial-level effects and participant-level variability, they do not explicitly model how emotional states unfold over time or how the probability of observing a given state depends on the immediately preceding one. MC modelling, by contrast, provide a principled framework for quantifying state-to-state transition probabilities, allowing us to examine patterns of FE expression activation during gameplay. Although the current literature does not supply prior studies applying first-order MCs directly to FER time-series, the affective-computing literature widely employs Hidden Markov Models (HMMs) to model temporal dependencies in emotion recognition tasks, including facial expressions [118]–[120], speech [121]–[123], and human affective states [124]. Similarly, transition matrix approaches have been used in affective gaming and human-computer interaction to analyze how players move between behavioural or psychophysiological states over time [125], supporting their use in characterizing temporal structure in emotionally driven interactions. Thus, *Step Ib* employs a MC-inspired approach as an interpretable and data-efficient method to quantify transitions between detected FE states during gameplay. Finally, in *Step II*, the analytical framework is extended by integrating HRV features into the GLMMs to jointly evaluate how FE and ANS-related physiological dynamics contribute to task performance.

1) Generalized Linear Mixed Models:

- *GLMM for Step Ia: behavioral analysis:* Given the repeated measurements of FE activation (one evaluation per second for each emotion), we used a GLMM to examine differences between the three samples across the two game modes (i.e., Snake and Matching Pairs). Specifically, in this study, the emotion variable was treated as a continuous dependent variable. Effect magnitudes are conveyed through standardized regression coefficients (β) and model F-statistics. Pseudo-R^2 indices were not reported for these models, as their interpretation is less straightforward in the context of high-frequency, multi-response GLMMs. GLMM was implemented using SPSS v.1.2.4.0. In the model, game type was treated as a condition, while emotion was the dependent variable. Cultural demographic information was included as a fixed factor, with Korea as the reference category. Model comparisons were conducted using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to evaluate model fit and prevent overfitting.

- *GLMM for Step II: multimodal domains integration:* In this step, GLMMs integrating FE and HRV-related features have been implemented to analyze their impact on task performance in the Snake and Matching Pairs games. Four separate GLMMs were developed for each game:

- A model including only FE-related features (*10*);
- A model encompassing only a 'canonical' set of HRV features, comprising time-frequency domain and entropy-based HRV features (*22*);
- A model including only a specific set of non-linear HRV features – namely 'complex' – comprising fractality, self-similarity, and recurrence quantification analysis (RQA) -derived measures (*10*);
- A model incorporating all previous features combined (*42*), reported in an extended form in the Supplementary document, Table A1.

All GLMMs implemented for this step (SPSS v.1.2.4.0) used a gamma distribution with a log link function for the dependent variables, given the skewed distribution of game performance scores in both the Snake and Matching Pairs games. Participants' cultural background was included as a random effect in all GLMMs. Preliminary analyses showed no significant differences in HRV features across cultural groups, consistent with the expectation that cardiovascular dynamics in healthy individuals show minimal cross-cultural variability. However, since culture had emerged as a potential confounding factor in the analysis of facial emotions, modelling it as a random effect allowed us to account for residual intergroup variability without assuming systematic differences attributable to cultural background. Model comparisons were conducted using the AIC and BIC to evaluate model fitting and avoid overfitting. Additionally, the Conditional R^2 (R^2_{cond}) was used to assess the model goodness-of-fit.

2) Continuous-State Markov Operator for FE Dynamics:

Traditional MC formulations describe a stochastic process evolving over a finite set of discrete states, with transitions characterised by a transition probability matrix. Classical MC models assume that, at each time step, the system occupies a single discrete state from a predefined set and that transitions between states satisfy the Markov property. In this study, we adopt a MC-inspired approach specifically tailored to the continuous emotional space generated by our FER system. Following Ekman's emotion taxonomy [30], [34], each time point is represented by a 7-dimensional probability vector associated with the canonical facial expressions (*angry, disgust, fear, happy, neutral, sad, surprise*). Instead of discretising these vectors into single emotion labels, we preserve their graded nature and model temporal dynamics directly within

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this continuous space. To characterise emotion transitions, we construct a *transition co-occurrence matrix* (TCM) by accumulating outer products of consecutive FE vectors (Eq. 5),

$$TCM = \sum_{n=1}^{N-1} [FE_n^T \times FE_{n+1}] \tag{5}$$

Each element $TCM_{i,j}$ quantifies the empirical co-activation between emotion component i at time n and component j at time $n+1$. After row-wise normalisation, the resulting matrix is interpreted as a *continuous-state Markov transition operator* acting on the emotional probability space. This operator captures temporal dependencies between FE distributions while avoiding the artificial discretisation imposed by classical finite-state MC models.

The resulting TCMs for both the Snake and the Matching Pairs games summarise the temporal evolution of each subject's emotional profile throughout the full task sequence while preserving the probabilistic structure of the FE outputs. Each TCM is then row-normalized with the sum of each row (Eq. 6):

$$T\hat{C}M = TCM \oslash TCM \times J \tag{6}$$

Where $\oslash$ denotes element-wise division, and J is the all-ones matrix. Finally, each element of the TCM represents the probability of moving from one emotional state to another. All main diagonal elements represent the probability of remaining in the same emotional state. All other elements represent the transition probabilities from one state to another. If one or multiple of the seven considered FE present a null probability of being reached, these are discarded from further analysis, and $T\hat{C}M$ size is reduced accordingly. Finally, the sub-chain probability (SC_P) is computed to account for possible transient states (*i.e.* states which have null probabilities of being reached in a finite number of steps).

From the SC_P continuous-state operator for each individual in both S and MP games, a total of ten standard Markov metrics were calculated as reported below:

- Entropy Rate (ER), which is calculated as reported in Eqs. 7 and 8 [126];

$$ER(SC_P) = \sum_i \mu_i e_i, \tag{7}$$

where:

$$e_i := -\sum_j p_{ij} \log p_{ij}, \tag{8}$$

is the entropy associated with each state and μ_i is the asymptotic distribution of the chain.

- Stability (St), which is computed as the mean values of the SC_P diagonal elements (Eq. 9)

$$St(SC_P) = \frac{\sum_{n=1}^{N} p_{i,i}}{N} \tag{9}$$

- Spectral Gap (SpG), which is the difference, in absolute values, of the two highest eigenvalues of the SC_P [127];
- Mean Hitting Time (MHT): considering the *i*-th FE, the MHT is calculated as the average of hitting times needed to reach the *i*-th FE for the first time, starting from any state. Seven MHT features (*i.e.*, one for each FE) were computed.

$$MHT_i(SC_P) = \frac{\sum_{n=1}^{N} mht_{i,n}}{N} \tag{10}$$

3) HRV and Related Features: In this study, HRV analysis was performed on ECG recordings sampled at different frequencies, depending on the population group: 250 Hz for Korean and Japanese cultural groups and 300.62 Hz for the Italian cultural group. ECG preprocessing included bandpass filtering to remove noise and baseline wander, followed by R-peak detection using the Pan-Tompkins algorithm [128], [129].

Once R-peaks were identified, the RR intervals were extracted, forming a sparse time series due to the non-uniform nature of cardiac rhythms. To obtain a continuous and analytically tractable representation of HRV, the RR interval time series was interpolated using the point process model developed by Barbieri et al. [130]. This approach establishes a probabilistic framework for real-time HRV dynamics. Specifically, Babieri's point process algorithm modeled the RR intervals as a stochastic process governed by an inverse Gaussian distribution, in which the instantaneous heart rate was estimated as a continuous function. The model parameters were iteratively optimized using maximum likelihood estimation to ensure a physiologically coherent reconstruction of the underlying autonomic regulation. This methodology provided a uniformly sampled HRV signal ($fs = 50Hz$) suitable for standardizing the feature extraction process across all subjects and performing subsequent analysis. HRV metrics were then computed across multiple domains: (i) time-domain features, (ii) frequency-domain metrics derived through spectral decomposition (Welch's method) to quantify power distribution across very-low-frequency (VLF), LF, and HF bands, (iii) entropy-based measures (approximate, sample, and distribution entropies), (iv) fractal and scale-free metrics, and (v) RQA-derived metrics to characterize the complexity and dynamical properties of heart rate fluctuations. As previously reported, separate GLMMs were estimated for the identified two HRV feature groups to analyse the data in a progressive complexity framework. The 'canonical' HRV metrics group, encompassing features from domains (i)–(iii), represents the first level of analysis, reflecting linear and physiologically established aspects of autonomic variability. Once this baseline level was characterised, a second GLMM was fitted for HRV features belonging to domains (iv) and (v), which reflect a higher level of dynamical and structural complexity in the RR series.

IV. Results

A. Results of Step Ia

The GLMM analysis of FE dynamics activation across Italian, Japanese, and Korean cultural groups during gameplay revealed distinct cultural patterns. The results showed that the Italian cultural group generally exhibited lower activation levels for negative FE, such as *angry* and *disgust*. In contrast, participants from Japanese and Korean cultural groups showed higher activation levels for these emotions. *Fear* was more prominent among Italians and Koreans cultural groups, with Japanese culture participants showing lower activation.

Happy was highly activated in the Italian culture group but was game-dependent for Japanese cultural group and notably low among the Korean culture group. *Neutral* FE activation also varied based on the game for all cultures. *Sad* was low for participants from Italian and Japanese cultural groups but highly activated among participants from the Korean culture group. Lastly, *surprise* was more frequently observed in the Italian culture group, whereas it was less pronounced in the Japanese and Korean culture groups. The Korean culture group served as the reference group throughout the analysis. Table I shows a detailed analysis of Snake game and Matching Pairs game between different cultural groups. The detailed analysis of FE during the Matching Pairs and the Snake game

TABLE I: FE Analysis by Country for *Matching Pairs* Game and *Snake* Game. *F* denotes the overall model F-statistic testing whether the regression model explains a significant proportion of variance in the dependent variable, β indicates the estimated regression coefficient representing the strength and direction of the relationship between variables and *t* is the corresponding t-statistic assessing the significance of each coefficient. $^{***} = p < 0.001$, $^{**} = p < 0.01$, $^{*} = p < 0.05$

Emotion	*Country*	*Matching Pairs Game*			*Snake Game*		
		F	β	*t*	*F*	β	*t*
Angry	Italy	264.7***	-3.83	-14.78***	278.41***	-3.24	-19.17***
	Japan		2.05	9.12***		0.42	2.71**
	Korea		Ref.	-		Ref.	-
Disgust	Italy	21.4***	-0.11	-6.47***	19.02***	-0.15	-4.36***
	Japan		-0.03	-2.07*		0.05	1.70
	Korea		Ref.	-		Ref.	-
Fear	Italy	82.0***	-0.02	0.38	120.58***	-0.01	0.11
	Japan		-0.58	-11.27***		-0.40	-13.52***
	Korea		Ref.	-		Ref.	-
Happy	Italy	139.9***	5.66	16.66***	50.07***	3.70	7.84***
	Japan		2.59	8.79***		3.95	9.24***
	Korea		Ref.	-		Ref.	-
Neutral	Italy	39.4***	1.21	2.44*	16.11***	2.87	5.58***
	Japan		3.75	8.72***		1.68	3.61***
	Korea		Ref.	-		Ref.	-
Sad	Italy	456.4***	-7.50	-24.37***	483.02***	-7.11	-28.23***
	Japan		-7.18	-26.89***		-5.74	-25.09***
	Korea		Ref.	-		Ref.	-
Surprise	Italy	428.0***	4.54	24.25***	381.43***	3.95	24.26***
	Japan		-0.61	-3.75***		0.04	0.24
	Korea		Ref.	-		Ref.	-

provides a deeper insight into these general patterns: For the *angry* FE, Italian cultural group showed a significantly lower activation probability ($\beta = -3.83, t = -14.78^{***}$) during the Matching Pairs game. Moreover, Japanese cultural group showed a significantly higher activation probability ($\beta = 2.05, t = 9.12^{***}$). For the Snake game, Italian cultural group again showed a significantly lower activation probability ($\beta = -3.24, t = -19.17^{***}$), while Japanese cultural group showed a smaller yet still significantly higher activation probability ($\beta = 0.42, t = 2.71^{**}$).

For the *disgust* FE cluster, during the Matching Pairs game, Italian cultural group showed a slightly lower activation probability ($\beta = -0.11, t = -6.47^{***}$), while Japanese cultural group also showed a lower activation probability ($\beta = -0.03, t = -2.07^{*}$), although less pronounced than the Italian cultural group. In the Snake game, the Italian cultural group continued to show lower activation probability ($\beta = -0.15, t = -4.36^{***}$). In contrast, the response of the Japanese cultural group was not significant ($\beta = 0.05, t = 1.70$).

The analysis of *fear* FE revealed a different pattern. In the Matching Pairs game, the Italian cultural group showed no significant change in *fear* FE ($\beta = -0.02, t = 0.38$). In contrast, Japanese cultural group exhibited a statistically significant lower activation probability ($\beta = -0.58, t = -11.27^{***}$). During the Snake game, Italian cultural group also showed no significant activation ($\beta = -0.01, t = -0.11$), but Japanese cultural group showed a marked lower activation probability in *fear* FE ($\beta = -0.40, t = -13.52^{***}$).

The *happy* FE cluster showed a highly increased activation probability in Italian cultural group during the Matching Pairs game ($\beta = 5.66, t = 16.66^{***}$), with Japanese cultural group also showing a significantly higher activation probability ($\beta = 2.59, t = 8.79^{***}$). In the Snake game, both Italian ($\beta = 3.70, t = 7.84^{***}$) and Japanese cultural group ($\beta = 3.95, t = 9.24^{***}$) continued to show significantly higher activation probability compared to Korean cultural group.

The *neutral* FE activation varied by game. During the Matching Pairs game, Italian cultural group participants showed a modestly higher activation probability ($\beta = 1.21, t = 2.44^{*}$), with Japanese cultural group showing a more significant response ($\beta = 3.75, t = 8.72^{***}$). In the Snake game, both Italian ($\beta = 2.87, t = 5.58^{***}$) and Japanese cultural group ($\beta = 3.18, t = 5.87^{***}$) exhibited significantly higher activation probability.

For *sad* FE, Italian cultural group showed a strong lower activation probability during the Matching Pairs game ($\beta = -7.50, t = -24.37^{***}$), and this trend continued in the Snake game ($\beta = -7.11, t = -28.23^{***}$). Japanese cultural group similarly showed substantial lower activation probability ($\beta = -7.18, t = -26.89^{***}$) in the Matching Pairs game and ($\beta = -5.74, t = -25.09^{***}$) in the Snake game.

Lastly, in the case of *surprise* FE, Italian cultural group showed significantly higher activation probability during both the Matching Pairs ($\beta = 4.54, t = 24.25^{***}$) and the Snake ($\beta = 3.93, t = 24.26^{***}$) games. In contrast, the Japanese cultural group showed a significantly lower activation probability in the Matching Pairs game ($\beta = -0.61, t = -3.75^{**}$) and no significant activation difference in the Snake game ($\beta = 0.04, t = 0.24$).

B. Results of Step Ib

Statistical analysis was performed to detect differences among the characteristic features of the TCMs across *different cultures* in the Snake and Matching Pairs games. Since the Shapiro-Wilk normality test (significance level $\alpha = 0.05$) rejected the null hypothesis for all features' distribution, the nonparametric Kruskal-Wallis test (significance level $\alpha = 0.05$) was implemented to test whether MC-related features of FE dynamics belonging to different cultures come from the same distribution. A post-hoc Tukey-Kramer correction was used to test multiple comparisons. Figures 4 and 5 summarise all significant cultural differences in MHTs. In the Snake game (Figure 4), cultural effects emerged for the *angry*, *disgust*, *fear* and *surprise* MHTs. For the *angry* FE, the Italian cultural group showed higher MHTs than both the Korean ($p < .001$) and the Japanese ($p < .001$) cultural groups; the associated effect size reflected a strong divergence across cultures ($d = 1.022$). For the *disgust* FE, the Italian cultural group again exhibited higher MHTs ($d = 0.487$) than both the Korean ($p < .05$) and the Japanese ($p < .05$) cultural groups. The *fear* FE condition showed a different configuration: Japanese cultural group displayed the highest MHTs with respect to Korean ($p < .05$) and Italian cultural group participants ($p < .05$, $d = 0.613$). Finally, for the *surprise* FE, both Korean ($p < .05$) and Japanese ($p < .001$) cultural groups showed higher MHTs, while Italians appeared faster and more consistent in their responses ($d = 0.82$). A similar pattern was found in the Matching Pairs game (Figure 5), where cultural modulation of MHTs was again evident across several emotional states. For the *angry* FE, the Italian cultural group confirmed their markedly higher MHTs compared to both the Korean ($p < .001$) and the Japanese cultural group ($p < .001$, $d = 0.868$). A similar pattern, though less pronounced with respect to the Snake game, was observed for the *fear* FE, where the Japanese cultural group displayed higher MHTs relative to their Italian counterparts ($p < .05$, $d = 0.467$). For the *sad* FE, the Korean cultural group generally exhibited the lowest MHTs, while the Japanese ($p < .05$) and Italian ($p < .05$) cultural groups showed higher values ($d = 0.58$). Finally, for the *surprise* FE, the Italian cultural group confirmed the trend demonstrated in the Snake game by displaying the lowest MHTs, whereas both

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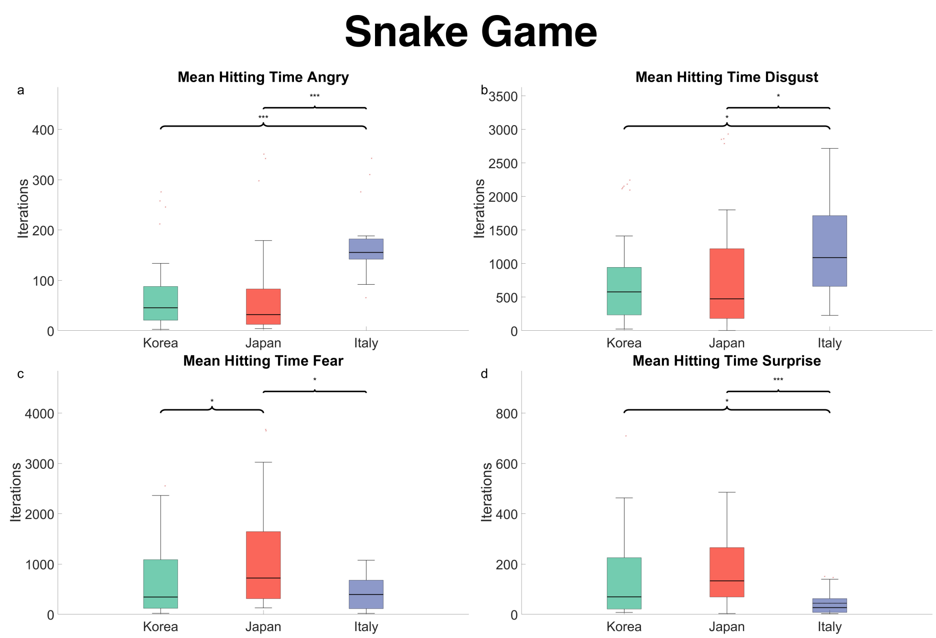

Fig. 4: Significant comparisons resulting from MC analysis on FE data across different cultures in the Snake game. $^{***} = p < 0.001$, $^{**} = p < 0.01$, $^{*} = p < 0.05$

the Korean ($p < .01$) and Japanese ($p < .001$) cultural groups showed consistently higher values ($d = 0.863$). No significant differences, in terms of MHTs, were observed for the *neutral* and *happy* FEs for both games.

Furthermore, PANAS mean scores were examined in relation to participants' performance, specifically evaluating their trends before and after both games. The statistical results of this analysis, obtained by performing the Mann-Whitney U-test, are summarized in the Supplementary document, Figure B1. Notably, high-performing players in the Snake game exhibited lower negative emotions both before ($p = .0265$, $d = 0.633$) and after ($p = .0161$, $d = 0.693$) gameplay, as well as increased positive emotions post-game ($p = .0351$, $d = 0.599$), compared to lower-performing participants. A similar trend was observed for the Matching Pairs game, where higher-performing individuals showed an increase in positive emotions after gameplay ($p = .0257$, $d = 0.637$). Subsequent analyses then explored differences in MC-related features between *high-scoring* and *low-scoring* individuals for both Snake and Matching Pairs games. Shapiro-Wilk normality test (significance level $\alpha = 0.05$) rejected the null hypothesis for all features' distribution, so the non-parametric Mann-Whitney U-test (significance level $\alpha = 0.05$) was used for statistical comparisons. The results are briefly reported in Table III, along with descriptive statistic parameters (median and interquartile ranges) for high-scoring and low-scoring players in Snake and Matching Pairs games. Statistical analysis results for significant comparisons are also reported as boxplots (see the Supplementary document Figures B2 and B3). Substantially, low-scoring players in the Snake game show lower MHT for the *happy* FE ($d = 0.691$) and higher MHT for the *neutral* FE ($d = 0.856$). Also, low-scoring players exhibit higher *ER* values with respect to high-scoring players ($d = 1.023$). In the Matching Pairs game, instead, high-scoring players have higher *SpG* ($d = 0.707$) with respect to low-scoring ones and also exhibit higher values for the *happy* ($d = 0.883$) and *surprise* ($d = 0.618$) FEs.

Lastly, the comparison of MC-related features across Snake and Matching Pairs games for all participants. Shapiro-Wilk normality test confirmed non-Gaussian distribution of data; therefore, the Mann–Whitney U test (significance level $\alpha = 0.05$) was used for statistical analysis. Results, reported in Supplementary document Figure B2, show higher *St* values for the Snake game ($p < .001$, $d = 0.816$), whereas in the Matching Pairs game, the *SpG* is larger ($p < .001$, $d = 1.071$). Also, the two video games differ for the *happy* FE, which is less prominent in the Matching Pairs game with respect to the Snake game ($p < .01$, $d = 0.478$) and, therefore, tends to have a later onset (in terms of MHT: $p < .001$, $d = 0.891$) in the emotional space of players.

C. Results of Step II

All GLMM results related to *Step II* are shown in Table II. GLMMs results on the Snake game indicate that both sets of HRV features are significantly related to task performance. However, the combined model provided the best fit, with the lowest AIC and BIC values, and achieved the highest R^2_{cond} (0.912). The significance of features encompassing both FE and HRV domains (WAF_ST, WAF_SPG, pNN50) suggests that incorporating multiple physiological features provides a more comprehensive representation of cognitive engagement during the Snake game.

GLMMs' results on the Matching Pairs game showed that HRV features significantly predicted task performance, particularly time-domain and entropy-related measures. The highest R^2_{cond} (0.687) was observed in the HRV 'complex' model, while the combined model did not show a substantial improvement in R^2_{cond} (0.655). This suggests that adding additional physiological metrics beyond the HRV 'complex' feature set did not necessarily enhance the model's predictive power. However, the combined model still provided the best overall fit based on AIC and BIC values, indicating a more balanced trade-off between complexity and explanatory power. Conversely, in the Snake game, no FE-related features were significant in the combined model.

The combined models for both games highlight the significant features influencing task performance. The Snake game demonstrated the highest predictive power across all features combined ($R^2_{cond} = 0.912$). In contrast, the Matching Pairs game showed that the HRV 'complex' feature set alone

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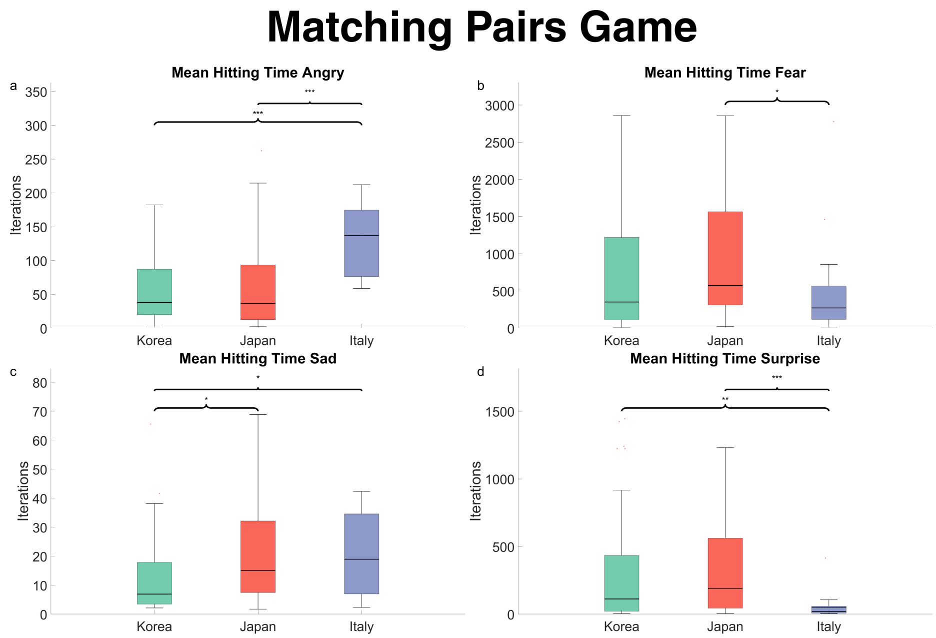

Fig. 5: Significant comparisons resulting from MC analysis on FE data across different cultures in the Matching Pairs game. $^{***} = p < 0.001$, $^{**} = p < 0.01$, $^{*} = p < 0.05$

accounted for most of the variance in performance ($R^2_{cond} = 0.687$). These results suggest that HRV-derived features, particularly those linked to entropy and recurrence patterns, play a crucial role in modulating cognitive performance during game tasks.

V. Discussion

Emotions are at the root of the human experience, shaping decision-making [131], social interactions [132], and overall well-being [133]. They serve as important indicators guiding individuals in managing complex social environments and responding to their daily challenges. Beginning in early childhood, FEs serve as a primary means of communication, playing a key role in bonding and survival by signaling needs and intentions to others [30], [36]. Understanding and recognizing emotional states is crucial, not only for personal fulfillment but also for supporting social connectivity and emotional engagement [134]. Emotions are also strongly conditioned by cultural norms and expectations, as different societies promote different ways of expressing and regulating emotional states [38], [67], [135]. Supporting this cultural perspective, Jack et al. [136] provided evidence that emotional expressions are not perceived and represented in a strictly universal manner across cultures. Specifically, their results showed that Eastern observers tend to rely more heavily on cues from the eye region when decoding emotional expressions and demonstrate less distinct clustering of the so-called basic emotions compared to Western observers. Moreover, they highlighted that cultural background shapes not only the intensity of facial expressions but also their temporal dynamics, including the timing and trajectory through which emotional information unfolds across facial regions. Taken together, these findings suggest that culturally grounded perceptual strategies and expression norms meaningfully influence how facial movements are produced and interpreted, challenging the assumption that FEs represent fixed, universally shared emotional signals.

Therefore, cultural variability also has direct technical implications for ML and FER. In particular, CNN-based FER systems may exhibit reduced accuracy and limited generalisability when trained on datasets that do not sufficiently capture cross-cultural diversity in facial movement patterns. This concern becomes especially relevant given the heterogeneity of datasets commonly used in the field: while large-scale, multicultural datasets such as RAF-DB [116], [117] and AffectNet [137] aim to provide broader demographic representation, widely used resources such as JAFFE [138], [139] remain culturally specific and limited in scope. Consequently, both dataset selection and methodological choices play a critical role in determining the extent to which FER models are culturally sensitive and capable of robust performance across diverse populations.

Beyond these methodological considerations, it is also essential to account for the functional role of specific emotions, as different emotional states are associated with distinct motivational and behavioural tendencies. Emotions such as *angry* and *disgust* are typically associated with an action-oriented response. *Angry*, in particular, as an emotion, is highly associated with a sense of empowerment, leading individuals to confront and challenge perceived injustices, thereby encouraging proactive behaviour and collective action for groups [140]. The association of *angry* and behaviour is so clear that some researchers have argued that it is almost self-evident, reflecting the natural tendency of anger to lead individuals to respond forcefully to threats or challenges [140], [141]. Similarly, *disgust*, although primarily a response to objects or actions perceived as harmful or repulsive, often elicits a strong drive to eliminate or distance oneself from the source, thereby reinforcing active interaction with the environment and individuals [142]–[144]. In addition, moral *disgust*, a type of *disgust* elicited by violations of moral or ethical norms, is correlated with anger, further emphasizing its role in driving action-oriented responses [145], [146].

In contrast, emotions such as *fear* and *sad* are more likely to lead to inhibition or disempowerment, resulting in passive or avoidant behaviour. *Fear*, for instance, is associated with avoidance rather than confrontation, leading individuals to withdraw from the perceived source of danger [140], [147], [148]. Furthermore, anxiety-realized *fear* can trigger a 'freeze' response, where the individual becomes unable to act or move, reflecting a more extreme form of passivity in the face of threats [149]. Likewise, *sad*, which is often associated with

TABLE II: GLMMs results for the Snake and the Matching Pairs games, with indications on the number of subjects included/excluded in each model, values of AIC, BIC and R^2_{cond}. Significant fixed effects are reported along with direction (+ = positive, $-$ = negative) and level of significance ($*** = p < 0.001$, $** = p < 0.01$, $* = p < 0.05$).

GAME / Feature Set	*Included/Excluded*	*Significant Fixed Effects*	*AIC*	*BIC*	R^2_{cond}
SNAKE GAME					
FE Feat.	-	-	-	-	-
HRV 'canonical' Feat.	105 / 4	pNN50* (-), ApEn*** (+), SampEn2*** (-), DistEn* (-)	21,09	25,725	0,874
HRV 'complex' Feat.	105 / 4	RR* (-), mean RT** (+), max RP path length* (+)	129,104	134,059	0,872
Combined	101 / 8	WAF_ST** (+), WAF_SPG** (+), pNN50* (-)	-7,552	-3,688	0,912
MATCHING PAIRS GAME					
FE Feat.	-	-	-	-	-
HRV 'canonical' Feat.	107 / 2	meanRR** (-), RMSSD* (+), TriRR* (+), stdDER1** (-), ApEn*** (-), SampEn2*** (+)	-69,906	-65,218	0,639
HRV 'complex' Feat.	107 / 2	mean RT** (+), max RP length** (-), TT* (-)	-7,045	2,045	0,687
Combined	94 / 15	meanRR* (-), mean RT* (+), max RP length* (-), TT* (-)	-89,346	-85,777	0,655

a sense of loss and lack of action, is typically characterized by passivity and a general slowing of the body, reducing motivation to action [150], [151].

A. Static Patterns of Facial Expressions Across Cultures

The *Step Ia* provides a broad, static overview by examining how the WAFER system detects FE across cultures during gameplay, establishing general cross-cultural patterns in outward emotional expression. Studies in the literature have consistently shown that culture plays a crucial role in influencing both emotional experiences and how these emotions are represented [37], [38], [67]. Furthermore, the degree to which these FE are displayed may also vary across cultures [38]. In this context, we have formulated three hypotheses to strengthen our study. The first of these hypotheses *(H1.1)* was "*Italian cultural group is expected to exhibit a higher probability of happy FE and a lower level of negative FE compared to Japanese and Korean cultural groups while playing Snake and Matching Pairs games*". Our results indicated that the Italian cultural group exhibited a higher probability of *happy* FE and a lower level of negative FE, thereby supporting H1.1 (see β values in Table I). Following the literature, Italian culture stands out among European cultures for its unique emphasis on pleasure and enjoyment, deeply rooted in its historical and cultural roots [68]. This hedonic form of cultural orientation [68] significantly affects various aspects of life, including motivations related to leisure activities, such as video games. Moreover, another study reports that 'entertainment' is a key reason people play video games, with Italian gamers dominating this aspect [69].

The second hypothesis *(H1.2)* in our research was, "*Japanese cultural group is expected to be less likely to show fear FE compared to Italian and Korean cultural group while playing Snake and Matching Pairs games*." Our results showed that the Japanese cultural group exhibited lower levels of *fear* of FE compared to the other groups, leading to the acceptance of H1.2 (see β values in Table I). These findings are consistent with the existing literature and can highlight how cultural norms shape FE in video game contexts. Moreover, in individualistic cultures, particularly in the West, authenticity is highly valued in various aspects of life [152]. However, in collectivist cultures, such as Japan, greater emphasis is placed on conforming one's behaviour to social expectations and avoiding inappropriateness [153]. This often involves "masking" emotions, a practice particularly evident in Japan's status-conscious society, where individuals tend to suppress expressions of *fear* [74]. Furthermore, cultural values such as fearlessness, integrity, and bravery are deeply rooted in Japanese traditions, such as Bushido and Buddhism [76]. These cultural values may have shaped the social norms surrounding emotional expression [77]. Although these philosophies do not explicitly mandate the suppression of *fear*, they have influenced the implicit rules of emotional display and may act as moderating factors in emotional regulation [135].

The third hypothesis *(H1.3)* was "*Korean cultural group is expected to be more likely to show negative FE compared to Italian and Japanese cultural groups while playing Snake and Matching Pairs games.*" Our findings highlighted that Korean participants expressed a higher frequency of negative FE, which supports H1.3 (see β values in Table I). The findings from the literature are consistent with our H1.3 results regarding FE in the Korean cultural group. For instance, the literature indicates that negative emotions are often expressed more frequently, both verbally and non-verbally, within Korean cultural contexts in response to various social and personal stimuli. Studies by M. Kim [80], [81] and Y. Kim [82] indicate that emotions such as *sad, angry, disgust*, and shame are frequently experienced, especially in circumstances involving personal failure, interpersonal betrayal, or interactions with people perceived as morally corrupt [83]. This tendency may be associated with the competitive dynamics inherent in Korean society, where individuals often face significant expectations and pressure to achieve success [84], [154]. In this context, competition (whether in academic settings, career advancement, or social interactions) can trigger frustration and heighten sensitivity to failure. Consequently, it can result in more negative emotional expressions than in other cultures.

B. Dynamic Evaluation of Facial Expressions Across Cultures

This step investigated the dynamic space of players' FE profiles, assessing how cultural background, emotional processing, cognitive performance, and game type shaped the timing of emotional responses. In *Step Ib*, the analysis focused on the continuous-state Markov operator derived from FE probabilities and, in particular, on the MHT. This metric provided a temporally resolved characterisation of emotional transitions that complements the static effects identified in *Step Ia*. Whereas the GLMM analysis quantified the extent to which each facial expression was activated, the MHT captured how quickly each emotion emerged during gameplay, revealing systematic differences across cultural groups, game types, and performance levels. Here, we investigated the cultural differences, testing whether groups from distinct cultural contexts showed statistical significant different temporal patterns in the MHT measure. Interestingly, cross-cultural variations emerged across both games. In the Snake game (Figure 4), Italian cultural group displayed delayed expressions of negative-valence emotions, particularly *angry* and *disgust* (Figure 4a,b), compared with the Korean and Japanese cultural groups. At the same time, the Italian cultural group showed a faster onset of *surprise* (Figure 4d), suggesting heightened reactivity to unexpected events in this fast, dynamic task. The

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TABLE III: $p-values$ resulting from statistical analysis to distinguish between high-scoring and low-scoring players at the Snake and Matching Pairs games, along with descriptive statistic parameters (median and iqr). $^{***}=p<0.001$, $^{**}=p<0.01$, $^{*}=p<0.05$

Game / Feature	ER	St	SpG	MHT Angry	MHT Disgust	MHT Fear	MHT Happy	MHT Neutral	MHT Sad	MHT Surprise
Snake $p-value$	$1.3\times10^{-3}*$	0.16	0.09	0.96	0.16	0.34	$3.2\times10^{-2}*$	$5.4\times10^{-3}*$	0.89	0.49
Snake $median_{high-scoring}$	0.85	0.15	0.97	48.82	697.30	517.70	61.90	1.06	14.89	78.96
Snake $iqr_{high-scoring}$	0.39	0.04	0.19	113.94	1054.23	657.55	155.14	0.16	22.64	158.90
Snake $median_{low-scoring}$	1.05	0.16	0.90	57.24	588.36	368.57	20.36	1.28	13.70	67.13
Snake $iqr_{low-scoring}$	0.54	0.04	0.24	110.88	941.61	985.56	99.96	0.48	26.03	162.30
Matching Pairs $p-value$	0.42	0.08	$1.7\times10^{-2}*$	0.27	0.19	0.14	$8.1\times10^{-3}*$	0.91	0.21	$4.1\times10^{-2}*$
Matching Pairs $median_{high-scoring}$	0.91	0.15	0.99	46.51	859.94	572.10	388.48	1.08	11.59	139.52
Matching Pairs $iqr_{high-scoring}$	0.43	0.01	0.03	95.60	970.47	1165.34	971.60	0.29	20.80	588.80
Matching Pairs $median_{low-scoring}$	0.92	0.15	0.98	37.56	621.06	371.54	70.19	1.06	12.77	55.87
Matching Pairs $iqr_{low-scoring}$	0.54	0.01	0.05	98.81	922.07	718.45	275.77	0.25	24.60	136.28

Japanese cultural group exhibited a consistent delay in *fear* (Figure 4c), confirming the pattern already noted in *Step Ia* and aligning with culturally shaped tendencies to modulate the expression of this emotion. Korean cultural group, by contrast, showed relatively shorter and more uniform MHT, indicating more stable expressivity across conditions. In the Matching Pairs game (Figure 5), similar cultural patterns were observed, but with a structure that reflects the task's slower, memory-oriented nature. Italian cultural group showed later *anger* and *sad* responses (Figure 5a,c), yet their *fear* and *surprise* responses were now faster than those of the Japanese cultural group (Figure 5b,d), whose *fear* delay persisted across tasks (Figure 5b). Koreans maintained comparatively rapid and consistent MHT, reinforcing their stable emotional response profile.

Moreover, these findings suggest that cultural background meaningfully shapes not only the intensity but also the timing and trajectory of emotional expressions [136]. Importantly, the direction and magnitude of these differences depend on the task's cognitive and emotional demands [56]. The Snake game, characterized by speed, uncertainty, and continuous threat detection, amplifies cross-cultural differences in rapid-reactivity emotions [155], [156]. In contrast, the Matching Pairs game relies on memory load, anticipation, and slower decision cycles, thereby highlighting cross-cultural differences in more deliberate or expectation-driven emotional responses. These observations are consistent with models distinguishing fast vs. slow emotional processes, i.e., rapid, reactive emotions emerge predominantly in time-pressured contexts. In contrast, slower, cognitively mediated responses are more evident in tasks requiring memory, planning, or sustained attention [157].

Complementary analyses on PANAS scores align with the existing literature [158], indicating that higher-performing players experience greater activation of positive emotions after the game sessions (see Figure B1 in the Supplementary document). Building on these self-reported differences, we investigated whether such affective patterns were also observable at the level of behavioral emotion dynamics, assessing whether cognitive task performance is reflected in differences in the MHTs of players' facial expressions, comparing how these emotion-specific durations vary between high- and low-scoring players. Notably, the faster transition to *happy* in low-scoring players may not indicate true positive affect but rather a reactive or involuntary emotional response, such as nervous laughter or smiling immediately after making a mistake [159]. Such expressions can serve as brief emotional releases or coping mechanisms under stress, as commonly observed in performance-failure situations [159]. Moreover, low-scoring players also demonstrated higher ER values in the Snake game. As ER reflects the unpredictability of transitions between emotional states, this increased variability in low-scoring players may indicate less consistent or more chaotic emotional regulation, potentially undermining their cognitive performance under pressure. Conversely, in the Matching Pairs game, high-scoring players showed higher SpG values, suggesting their emotional state transitions stabilize more rapidly. In the context of MC modeling, a larger SpG signifies a faster convergence to a steady emotional pattern, an attribute that may support sustained attention and better decision-making. Additionally, high-scoring players in the Matching Pairs game exhibited higher MHTs for the *happy* and *surprise* expressions, implying a more prolonged trajectory to these states. This may reflect a more controlled or deliberate emotional response, possibly indicative of better cognitive engagement and focus. These findings suggest that FER-derived MC metrics can meaningfully differentiate emotional processing styles linked to performance levels. High-scoring players tend to exhibit more stable and structured emotional dynamics traits, likely conducive to better cognitive control and game performance. In contrast, low-scoring players appear to experience more volatile and less regulated emotional patterns, which may hinder cognitive efficiency.

Finally, we investigated if the type of game influenced the dynamics of players' facial expressions. The MC model–based analysis showed greater emotional stability between consecutive states in Snake compared to Matching Pairs, and the emotional space available for exploration in Snake was more limited than in Matching Pairs. This reduction in emotional space, combined with increased stability, can be interpreted as a way to focus more on the game itself. Additionally, in the Snake game, there was a higher prevalence of positive emotions (i.e. *happy*), both in terms of presence and latency, according to Ferro et al. [160], which reported that the positive emotions experienced by gamblers do not show differences between the different types of games, as these seem more linked to a more internal connection with the game.

C. Combining FE and HRV Data to Model Gameplay Performance

GLMM analysis of the Snake and Matching Pairs games reveals profound insights into the interactions among FE, "canonical," and "complex" HRV feature sets in predicting cognitive outcomes. For the Snake game, FE features alone could not predict performance; however, both HRV feature sets demonstrated strong explanatory power, as evidenced by high R^2_{cond} values (Table II). Among these, entropy measures (*ApEn*, *SampEn*, and *DistEn*) and RQA-derived features (*recurrence rate*, *mean recurrence time*, and *max recurrence plot path length*) stood out as significant fixed effects (Table II). These findings underscore the intricate relationship between cardiovascular dynamics and cognitive processes, emphasizing the role of autonomic regulation in shaping task performance. The integration of FE and HRV features for the Snake game significantly enhanced the R^2_{cond}, reaching a value of 0.912 (Table II). In this combined model, FE-related features (*WAFERSt* and *WAFERSpG*) emerged as

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significant predictors alongside *pNN50* from the 'canonical' HRV features set (Table II). The inclusion of *pNN50*, a time-independent HRV measure, confirms its robustness as a marker of cognitive performance. A recent study on stress and cognitive performance found that reduced HRV, as measured by pNN50, was associated with better performance under stress. High-performing individuals showed greater parasympathetic recovery after stress, which could be linked to their ability to maintain performance under pressure [161]. These results point to the critical role of emotional and cardiovascular markers in understanding cognitive load, revealing a dynamic interplay between emotional states, autonomic regulation, and task demands, as changes in HRV, particularly in the context of mental stress, have already been linked to changes in cognitive load and emotional states [162]. Such findings raise pivotal questions about the modulation of cardiovascular activity during video gameplay, particularly regarding how shifts in sympathovagal balance, as captured by HRV and FE data, reflect cognitive engagement and adaptability across varying task conditions. For the Matching Pairs game, a similar analytical framework was employed. Even for the Matching Pairs game, GLMM analysis relying solely on FE-related features was insufficient for predicting cognitive outcomes, while 'canonical' and 'complex' HRV domains yielded significant insights II. Time-domain (*meanRR*, *RMSSD*, *TriRR*, and *stdDER1*) and entropy-related measures (*ApEn* and *SampEn*) from the 'canonical' HRV feature set, along with RQA metrics (*mean recurrence time*, *max recurrence plot path length*, and *trapping time*) from the 'complex' HRV feature set, emerged as pivotal predictors (Table II). These results solidify the relevance of advanced HRV analyses in assessing cognitive performance, particularly in tasks requiring sustained attention and cognitive stability [163]. Interestingly, the combined GLMM for the Matching Pairs game did not improve the R^2_{cond}, which remained at 0.655 (Table II). Despite this, the importance of RQA-derived features (*mean recurrence time*, *max recurrence plot path length*, and *trapping time*) and *meanRR* was reaffirmed (Table II). This suggests that while FE metrics played a less prominent role in the Matching Pairs game, autonomic markers reflecting recurrent and stable patterns were critical for understanding task-related performance. These findings provide compelling evidence for the role of autonomic dynamics in characterizing cognitive load [164], with features like *meanRR* and entropy measures serving as robust markers of task-specific physiological regulation. The results underscore the broader impact of cardiovascular activity modulation during gameplay, revealing task-specific patterns of autonomic regulation and emotional engagement [165]. For the Snake game, the interplay between recurrent autonomic patterns and emotional stability highlights the importance of adaptive sympathovagal balance in navigating cognitively demanding tasks. Conversely, the Matching Pairs game's reliance on stable autonomic markers suggests a need for consistent cognitive focus and physiological steadiness. These distinctions have profound implications for understanding how autonomic dynamics and emotional states shape cognitive performance in interactive and high-stakes environments. From a translational perspective, these findings have significant potential for informing the design of interventions and adaptive technologies. By leveraging the interplay between cardiovascular activity and emotional markers, it may be possible to develop personalized gaming or training platforms that optimize cognitive performance and emotional resilience. Furthermore, integrating these insights into real-world applications, such as neurorehabilitation and cognitive training programs, could pave the way for innovative strategies to enhance neuroplasticity, functional connectivity, and overall cognitive health.

VI. Implications, Future Studies and Limitations

The outcomes of this study provide important insights for game designers, who can use these findings to create more engaging and culturally immersive gaming experiences. By understanding how emotions are expressed differently across cultures, designers can adapt game elements to appeal more to different players, increasing both entertainment and immersion. Emotions, especially negative ones, are crucial in shaping players' experiences. Thus, the emotional impact of a game goes beyond its content and extends to how it triggers emotions; this study provides a basis for considering these factors within regulatory frameworks for game design, potentially guiding industry standards for how games manage emotional responses. In addition, the biosignal findings have practical implications for performance-oriented activities such as eSports, where emotional regulation and physiological responses directly affect player performance. Incorporating these findings into training and game design could help foster better mental resilience and control, leading to improved outcomes in competitive settings.

Future studies could benefit from including a wider range of cultural groups to deepen our understanding of how emotional expressions and experiences during gameplay differ across cultural backgrounds. By including participants from different regions, researchers may uncover more complex and culturally specific responses. In addition, expanding the physiological measures to include EEG and Photoplethysmography data could provide a more comprehensive view of players' emotional and physiological states, complementing existing facial expression data. Integrating eye-tracking technology with advanced facial expression recognition systems would further refine emotional assessments, enabling more accurate interpretation of participants' reactions during gameplay. This multimodal approach could lead to a deeper understanding of the interactive dynamics between cultural factors, physiological responses, and emotions in gaming contexts.

Moreover, future studies could also consider the natural characteristics of emotion datasets, as emotions such as happiness are often more easily repeatable than others. This tendency, which is commonly observed across multiple datasets in the literature, may contribute to distributional imbalances. Addressing such dataset-related issues through augmentation or resampling techniques could further strengthen the robustness of future findings.

There are several limitations to this study. First, using only two casual video games may limit the range of emotions elicited in participants, because casual games generally evoke less intense emotional responses than more complex and immersive games. This limitation is particularly relevant for emotions such as disgust and fear, which typically emerge in richer contexts that contain stronger narrative, threat-related, or sensory cues. Consequently, our findings may not be generalizable to other video games. Nevertheless, this study represents an initial step in examining cross-cultural differences in emotional and physiological responses. The use of casual, comparable games provided a controlled setting for this initial exploration. Taken together, these considerations may also help explain why the features of FEs were not predictive of performance. Future research should include more complex game genres to assess whether similar patterns emerge when emotions are elicited under greater cognitive and emotional demands.

A methodological limitation of the present work is associated with the adopted Markov-inspired approach. The transition operator was derived from continuous FE probability vectors rather than from strictly discrete emotional states. As a result, the model should be interpreted as a Markov process over probabilistic emotional profiles, rather than as a classical finite-state emotion MC. This continuous-state formulation is well suited to the graded nature of FE outputs and allows for a principled characterisation of temporal dependencies, but future research could compare this approach with models based on discrete emotional labels or on clustered latent states to evaluate potential differences in interpretability and sensitivity. Another limitation of the present study is the gender imbalance in the Korean and Japanese participant samples, with a noticeably lower number of female participants than males. This uneven distribution may influence the interpretation of culture-specific effects, as the observed differences could be disproportionately driven by the male subsample.

In addition, the emotion recognition model used is inherently a 'black box', meaning that its internal processing is not easily interpretable. This lack of transparency makes it difficult to fully understand how the model detects and classifies emotions from facial expressions, potentially limiting insight into specific emotional nuances that vary across cultures. Lastly, the interpretation of the emotion surprise is inherently context-dependent. Unlike emotions with clear positive or negative valence, such as happiness or sadness, surprise can emerge in response to both pleasant and unpleasant situations, including happy achievements or sudden failures. This contextual variability makes it more difficult to consistently categorize surprise. As a result, facial expression recognition systems may struggle to accurately interpret surprise, potentially overlooking the emotional nuance conveyed by the expression. This limitation is especially relevant in cross-cultural settings, where similar facial expressions of surprise may convey different meanings based on cultural norms and situational expectations.

VII. Conclusion

Following the findings of *Step Ia*, which highlighted cultural differences in the levels and types of emotional expression, *Step Ib* was designed to explore how emotions change dynamically during gameplay. While *Step Ia* focused on static emotional expressions, *Step Ib* explores the dynamic nature of emotions and how they change from one state to another in response to in-game events. One important factor considered in this study is performance. Previous literature suggests that an individual's performance during an activity can significantly influence the emotions they experience [166], [167]. These findings highlight the significant role of emotional factors in influencing players' performance. This is corroborated by the findings of *Step II*, which reveal distinct cardiovascular dynamics, particularly an imbalance in sympathovagal balance when players engage in cognitive tasks such as those posed by the proposed video games. The sympathetic and parasympathetic systems are differentially activated depending on the task's cognitive load. Moreover, the nature of the video game plays a crucial role in shaping these physiological responses. The type of cognitive processing required, whether it involves reactive decision-making, reflective thinking, rapid information processing, or memorization and sustained attention, affects cardiovascular dynamics. Players appear to adjust their parasympathetic activity, particularly vagal tone, in response to the cognitive demands of the game, optimizing their physiological state to enhance performance. These findings suggest a dynamic interaction between emotional regulation, cognitive processes, and ANS activity in video game performance.

Author contributions statement

Conceptualization, A.L., A.G., and M.C.G.; methodology, A.G., P.T., M.C.G, and A.L.; investigation, P.T., A.L., and M.C.G.; data curation, P.T., F.C., L.F., M.D., K.P., R.T., X.Y., A.G, A.L, and M.C.G; writing—original draft preparation, M.C.G., P.T., M.D., and A.L.; writing—review and editing, M.D., M.C.G., R.T., A.G., P.T., Y.X., and A.L.; supervision, A.G., R.T., M.D, and A.L. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

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Disclosure Statement

There is no conflict of interest.

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