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Research Article

Assessment of Learners' Motivation during Interactions with Serious Games: A Study of Some Motivational Strategies in Food-Force

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This study investigated motivational strategies and the assessment of learners' motivation during serious gameplay. Identifying and intelligently assessing the effects that these strategies may have on learners are particularly relevant for educational computer-based systems. We proposed, therefore, the use of physiological sensors, namely, heart rate, skin conductance, and electroencephalogram (EEG), as well as a theoretical model of motivation (Keller's ARCS model) to evaluate six motivational strategies selected from a serious game called Food-Force. Results from nonparametric tests and logistic regressions supported the hypothesis that physiological patterns and their evolution are suitable tools to directly and reliably assess the effects of selected strategies on learners' motivation. They showed that specific EEG "attention ratio" was a significant predictor of learners' motivation and could relevantly evaluate motivational strategies, especially those associated with the *Attention* and *Confidence* categories of the ARCS model of motivation. Serious games and intelligent systems can greatly benefit from using these results to enhance and adapt their interventions.

1. Introduction

It is widely acknowledged that learners' psychological and cognitive states have an important role in intelligent systems and serious games (SGs). For instance, engagement and motivation or disaffection and boredom obviously affect learners' wills and skills in acquiring new knowledge [1]. SGs cannot, therefore, ignore these states and should take them into account during learning process. One important learners' state is motivation which plays a crucial role in both the learners' performance and the use of intelligent systems over time [2]. Motivation is generally defined as that which explains the *direction* and *magnitude* of behaviour, or in other words, it explains *what* goals people choose to pursue and *how* they pursue them [3]. It is considered as a natural part of any learning process. Several researches have showed that motivated learners are more likely to be more engaged, to undertake challenging activities, and to exhibit enhanced performance and outcomes [4, 5]. Therefore, it is of particular relevance to study motivation and its role in improving learners' performance during gameplay.

Learners' interactions with Intelligent Tutoring Systems (ITSs) and especially SGs have always been considered to be intrinsically motivating. One possible explanation is the fact that ITSs generally use pictures, sounds, videos, and so forth, that are considered, crudely, as motivational factors. Intrinsic motivation is possibly gained through challenge, curiosity, control, sensory stimuli, interaction, and fantasy when using SGs [6, 7]. However, many researchers have argued that learners' negative emotions or amotivational states such as boredom or disengagement have been known to appear following a certain period of interaction with computer systems. These states can be overwhelming to learners and cause motivational problems and decrease learning benefits [2, 8, 9]. Once learners' psychological and cognitive states are identified, intelligent systems are in a much better position to act upon them. In this perspective, several studies have described intelligent systems that can provide adapted emotional or cognitive strategies for coping with, or at least reducing, the negative learners' states [8–12]. Computer systems can also use motivational strategies which are the actions (or tactics) taken in order to scaffold learners' motivation toward tasks and goals of learning process and to make learning easier, faster, more enjoyable, more self-directed, and more effective. However, it is surprising to find so little mention of the motivational strategies and relatively little is known about coping with motivational problems, which motivational strategies should be used, and to what extent they are employed. Within the researchers who have tackled this issue, some have found that SGs seemed to show a promising potential from a motivational standpoint. It has been consistently shown that SGs have inherent motivational properties and different strategies, allowing them to be used for improving educational applications [7, 13–15]. Game designers, for example, employ a range of Artificial Intelligence (AI) techniques (e.g., controlling the behaviour of the nonplayer characters, providing performance feedback) to promote long-term user engagement and motivation [16].

Moreover, evaluating systems interventions is obviously related to differences in learners' performance (successful completion of tasks) or judgement (self-report questionnaires). However, by using only performance or judgement in evaluating motivational strategies, intelligent systems risk obtaining delayed or imperfect evaluations or interrupting learning process by repeatedly using self-report questionnaires. This may offer misleading information regarding the impact of motivational strategies on learners' motivation. Therefore, it is of particular relevance to investigate new ways of evaluating motivational strategies. One promising way is the use of physiological sensors. This is notably explained by the significant results of recent studies involving physiological sensors to assess motivational learners' states as well as emotional and cognitive systems strategies [10, 17–19].

The present paper examines the implication of different physiological sensors to evaluate some motivational strategies employed in SGs and to highlight the corresponding learners' patterns. To this end, we use an existing SG called Food-Force presented by the United Nations World Food Programme (WFP) and intended to learn players about the fight against world hunger. The ultimate objective of this intervention study is to assess learners' motivation when motivational strategies haves been used by SGs. We ask the two following research questions: Can we empirically find physiological patterns to evaluate the effects of motivational strategies on learners' motivation during interactions with Food-Force? If so, Can these patterns feed AI models to predict the level of learners' motivation to the motivational strategies? Hence, two hypotheses are postulated: (1) it is possible to model learners' physiological reactions and trends towards motivational strategies in an SG environment and (2) we can discriminate between effective and ineffective motivational strategies using physiological manifestations as well as self-report questionnaires. We designed an experiment using an existing SG called Food-Force and combined both the theoretical ARCS model of motivation and empirical physiological sensors (heart rate (HR), skin conductance (SC), and electroencephalogram (EEG)) to assess the effects of motivational strategies on learners.

The organization of this paper is as follows. In the next section, we present previous work related to our research. In the third section, we explain our empirical approach in assessing learners' motivation. In the fourth section, we describe the theoretical ARCS strategies to support motivation and the studied strategies in Food-Force. In the fifth section, we detail our experimental methodology. In the sixth section, we present the obtained results and discuss them. Finally, we give a conclusion in the last section, as well as present future work.

2. Related Research

Csikszentmihalyi [20] observed that people enter in a "flow" state when they are fully absorbed in activity during which they lose their sense of time and have feelings of great satisfaction. Games generally catalyze conditions of flow state by their clear goals, balance between challenges and skills, immediate feedback, progress, and control. Furthermore, Ryan and Deci [21] defined the Self-Determination Theory (SDT) and distinguished between intrinsic motivation (to understand the subject) and extrinsic motivation (for the reward of a certificate or employment). They assumed that the individual is normally inclined to be active, motivated, curious, and eager to succeed. They also recognized that some people mechanically perform their tasks, or even people passive and unmotivated. They reported that environments that facilitate the satisfaction of psychological needs can boost the internal dynamism of people to maximize their motivation and to maximize results in personal development and behavior. Ryan and colleagues [22] have studied the SDT and stated that the motivational pull of computer games is attributed to the combination of optimal challenge and informational feedback. Bartle [23], one of the pioneers of the massively multiplayer online games and known for his work on the first MUD (An MUD (originally Multiuser dungeon, with later variants Multiuser Dimension and Multiuser Domain) is a computer program, usually running over the Internet, that allows multiple users to participate in virtual-reality role-playing games.), distinguished several motivational profiles among players: the killer (competitiveness), the per-former (success), the explorer (curiosity), and socializer (cooperation). He reported that some players strive to achieve all the challenges offered by the gameplay while others seek the company of other players, or want to discover the whole virtual world.

Nevertheless, the effectiveness of any study regarding the assessment of learners' motivational states depends on two important factors: (1) the choice of proper assessment tools and (2) the accuracy of the selected tools. For example, Schunk et al. [5] used Keller's ARCS model (see next section for a description of this model) and proposed several rules to infer motivational states from two sources: the interactions of the students with the tutoring system and their motivational traits. Some researchers have analyzed log files and have established correlations between learners' actions in log files and their motivational states (e.g., [24]). Other researchers have used physiological sensors to assess learners' motivation and correlate physiological learners' responses to some dimensions of motivation such as attention and confidence (e.g., [17, 25]). They have identified that the combination of various physiological sensors may provide perfect measures of learners' states and consequently enhance systems intervention strategies. They have involved a variety of sensors to assess physiological learners' states and responses to stimuli in Computer-Based Education (CBE) environment: mouse, electromyogram (EMG), respiration (RESP), HR, SC, and more recently EEG. For instance, Conati [19] has used biometric sensors (HR, SC, EMG, and RESP) and facial expression analysis to develop a probabilistic model of detecting students' affective states within an educational game. Arroyo and colleagues [26] have used four different sensors (camera, mouse, chair, and wrist) in a multimedia adaptive tutoring system to recognize students' affective states and embed emotional support.

Others studies have shown that learners have also been known to experience a lower sense of relatedness to the educational systems [27], thus increasing their feeling of isolation and possibly leading to further motivational issues. For example, learners lack the substantial self-monitoring skills that CBE systems require and possibly start "gaming" the system [9]. In addition, CBE systems generally place fewer restrictions on learners and learners must take greater responsibility for their educational experiences. Hannafin and colleagues [28] recommended that students need more support and must be empowered to acquire the necessary skills to effectively progress in an educational environment. For example, it has been found that when collaborative learning strategy is used, a fewer errors are made than in individual learning situations, resulting in better outcomes performance, increased confidence, and decreased frustration levels of the learners [29, 30]. Dörnyei [31] has reported that motivational strategies are used not only to maintain students' motivation but also to generate and increase it. He has defined that more than one hundred motivational strategies can be used by teachers in the classroom. These strategies integrate the creation of the basic motivational conditions, the generation of initial motivation, the maintaining and the protection of motivation, and the encouragement of positive and retrospective self-evaluation. Furthermore, efforts to overcome learners' motivational problems have mainly been focused on tutor's strategies or instructional design aspects of the systems. For example, Hurley [12] developed interventional strategies to increase the learner's self-efficacy and motivation in an online learning environment. She extracted and then validated rules for interventional strategy selection from expert teachers by using an approach based on Bandura's Social Cognitive Theory and by observing the resulting learners' behaviour and progress. Goo and colleagues [32] showed that tactile feedback, sudden view point change, unique appearance and behaviour, and sound stimuli played an important factor in increasing students' attention in virtual reality experience. Arroyo and colleagues [8] evaluated the impact of a set of noninvasive interventions in an attempt to repair students' disengagement while solving geometry problems in a tutoring system. They claimed that showing students' performance after each problem reengages students, enhances their learning, and improves their attitude towards learning as well as towards the tutoring software.

3. Assessment of Learners' Motivation

There are a few studies that have particularly considered the evaluation of motivational strategies. It is of particular significance for this research work that motivational strategies are identified and their impacts on learners are evaluated in a specific CBE environment, precisely serious games. In addition to ARCS self-reported questionnaires, the present study uses three physical sensors (SC, HR, and EEG) to assess motivational strategies while interacting with a serious game called Food-Force. We first need to present the tools used to measure motivation itself.

3.1. ARCS Model of Motivation. In the present study, the ARCS model of motivation [33] has been chosen to theoretically assess learners' motivation in SG. Keller used the existing research on psychological motivation to identify four components of motivation: *Attention*, *Relevance*, *Confidence*, and *Satisfaction*. His model has been used in training and games and has also been validated in numerous studies with all education levels and in many different cultures (e.g., [3, 34, 35]), and therefore, it is of particular interest in our study.

(i) *Attention:* to attract learners' attention at the beginning and during the process of learning. Diverse activities should be considered to maintain students' feelings of novelty thus the attention can be sustained.

(ii) *Relevance:* to inform learners of the importance of learning and to explain how to make the learning meaningful and beneficial.

(iii) *Confidence:* to allow learners to know the goal and to believe that the goal can be achieved, if enough effort (physical and/or intellectual) has been made.

(iv) *Satisfaction:* to provide feedback on performance and to allow learners to know how they are able to perform well and apply what is learned in real life situations.

The ARCS questionnaire asks students to rate ARCS-related statements in relation to the instructional materials they have just used. Examples of items related to each ARCS component are as follows.

(i) "uses questions to pose problems or paradoxes." (*Attention*);

(ii) "uses language and terminology appropriate to learners and their context." (*Relevance*);

(iii) "provides feedback on performance promptly." (*Confidence*);

(iv) "makes statements giving recognition and credit to learners as appropriate." (*Satisfaction*).

3.2. Physiological Sensors. Considering the motivation as a state of both cognitive and emotional arousal, we have decided to combine several noninvasive physiological sensors in order to empirically evaluate the motivational strategies in serious games context. Besides the SC and HR sensors which are typically used to study human affective states [36], we have considered relevant to use the EEG sensor in our proposed approach. Indeed, brainwave patterns have long been known to give valuable insight into the human cognitive process and mental state [37]. More precisely, our EEG analysis relies on differences between slow and fast wave ratios (i.e., "attention ratio" or Theta/low-Beta) which are correlated with responses to motivational stimuli and emotional traits [38, 39]. For instance, low-level attention is characterized by "a deviant pattern of baseline cortical activity, specifically increased slow-wave activity, primarily in the Theta band, and decreased fast-wave activity, primarily in the Beta band, often coupled" [40]. The power of the EEG "attention ratio" can be explained by Putman and colleagues [39]. According to the authors, a negative correlation exists between the attention ratio and learners' *Attention* level. A high Theta/low-Beta ratio is usually correlated with excessive Theta and consequently inattentive state. Conversely, a low Theta/low-Beta ratio is normally correlated with excessive Low-Beta brainwave activity reflecting normal state in adults.

4. Motivational Strategies

The key issue in this paper is related to the identification and assessment of motivational strategies in SGs that support and enhance learners' motivation. We define a motivational strategy as the use of a game element (or factor) [41] susceptible of providing motivational support for players. Motivational strategies in SG are the key to finding and harnessing players' motivation to learn and achieve their goals. For example, a virtual companion in SG can offer encouragement to players as well as offering additional aid in their current task. This is can be considered as a motivational strategy related to the *Confidence* category of the ARCS model only if it increases learners' belief in competence and consequently their effectiveness. Otherwise, it is simply an SG element and not a motivational strategy. Each of the four categories has also subcategories that are useful in identifying learners' motivational profiles and in creating motivational tactics (or strategies) that are appropriate for specific situations in SG [3].

Attention Getting Strategies (Capture Interest, Stimulate Inquiry, and Maintain Attention). Before any learning can take place, the learner's attention must be engaged. The challenge with the attention is to find the right balance of consistency, novelty, and understanding how people differ, what tactics to use, and how to adjust the tactics for the learners and how the tutor will be able to keep them focused and interested.

Relevance Producing Strategies (Relate to Goals, Match Interests, and Tie to Experiences). It is very difficult for students to be motivated to learn if they do not perceive there to be any relevance in the instruction. To stimulate the motivation to learn, it is best to build relevance by connecting instruction to the learners' backgrounds, interests, and goals.

Confidence Building Strategies (Success Expectations, Success Opportunities, and Personal Responsibility). When people believe that they have little or no control over what happens to them, they experience anxiety, depression, and other stress-related emotions. In contrast, when they believe that they can predictably influence their environment by exercising their efforts and abilities in pursuit of their goals, then they are more motivated to be successful.

Satisfaction Generating Strategies (Intrinsic Satisfaction, Rewarding Outcomes, and Fair Treatment). One of the most important elements of satisfaction is intrinsic motivation; that is, if learners believe that they achieved a desirable level of success while studying topics that were personally meaningful, then their intrinsic satisfaction will be high. Another component of satisfaction is based on social comparisons and comparisons to expected outcomes.

The present study invited participants to play the freely downloadable SG called Food-Force [42]. It is an initiative of the World Food Program (WFP) of the United Nations intended to educate players about the problem of world hunger. Food-Force is comprised of multiple arcade-type missions, each intended at raising players' awareness towards specific problems regarding worldwide food routing and aid. Food-Force also presents players' objectives in a short Instructional Video before the beginning of each mission. A virtual tutor also accompanies the player throughout each mission by offering various tips and lessons relative to the obstacles and goals at hand. All participants have never played Food-Force before. We have investigated in details six motivational strategies in Food-Force in order to answer our main research question. (Can we empirically find physiological patterns to evaluate motivational strategies during serious game play?) These strategies are related to the four categories of the ARCS model, see Figure 1.

Problem Solving. Keller's ARCS motivation theory tells us that the learner's motivation is also aroused by the mean of "solving a problem or resolving an open issue..." called inquiry arousal. Mission 2 (nutritious meal preparation) presents to learners a challenging problem that consists of finding the right combination of different food items (rice, beans, vegetable oil, sugar, and iodized salt) to create a nutritious and balanced diet, all at a target cost of 30 US cents per person per meal. It has been investigated in our experiment to study the Problem Solving strategy used by Food-Force.

Alarm Trigger. According to Brophy [43], situational interest is triggered in response to something in the situation (e.g., unexpected sound) that catches our attention and motivates us to focus on it and explore it further. Keller's ARCS motivation theory also argues that the learner's motivation

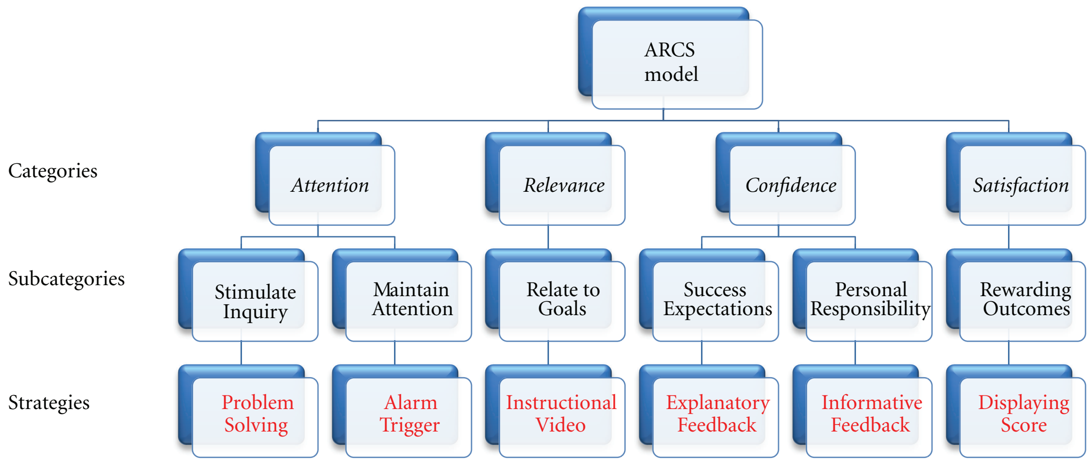
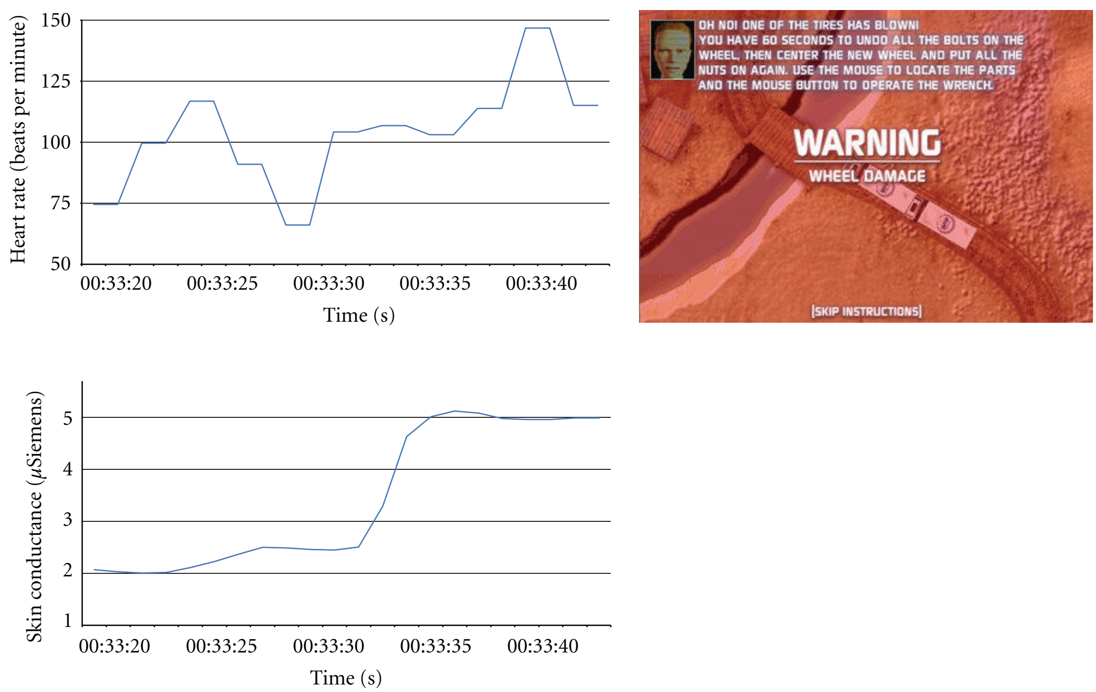


Figure 1: ARCS model and the corresponding motivational strategies.



EEG Theta/Low-Beta
F3: 1.25
C3: 0.98
Pz : 1.36

Figure 2: Alarm Trigger screen shot (mission 5 of Food-Force) and three physiological data (HR, SC, and EEG "attention ratio").

is possibly gained by a perceptual arousal (novel, surprising, or incongruous events). We have decided to investigate the three Alarm Triggers as a strategy supporting motivation in mission 5 (UN. food delivery) of Food-Force. An example of an alarm trigger is shown in Figure 2.

Instructional Video. Motivational strategies rely on some game elements that make a lesson content relevant to the learners. Keller has reported that the instructor has to tie instruction into the learner's experience by providing examples that relate to the learner's work. In Food-Force, Instructional Video segments that draw on players' existing knowledge have been used in order to show them the real application of presented mission in the field and connect each mission to the problem of world hunger.

Informative Feedback. It is important to raise learner's confidence by offering suitable feedback. According to [44], negative or positive Informative Feedback tells learners what they are doing. It works much better then Controlling Feedback which simply tells them what to do. For Informative Feedback used in Food-Force, comments like "What was a dangerous drop! Try to be more accurate and watch the wind gauge" (mission 3) or "Won't arrive immediately, but that might be ok for you" (mission 4) indicate the effects (or benefits) of actions taken by the player.

Explanatory Feedback. The learner is open to a brief instructional explanation that will help build the right mental model and/or correct misconceptions. Explanatory Feedback resulted in much better learning than Corrective Feedback [45], which can be automated in many authoring tools with only a few key strokes. The virtual companion of Food-Fore makes comments, such as "Rice: we need a lot of rice. It provides nutrition and energy" (mission 2), to explain user actions.

Displaying Score. Motivational strategies aimed at increasing learner's satisfaction usually focus on allowing students to display their work, encouraging them to be proud of themselves and celebrate success, and using rewards. Displaying Score strategy is used at the end of each mission in order to show players their current scores and their overall progress.

5. Experimental Methodology

5.1. Procedure. Thirty-three volunteers (11 females) took part in the study in return of a fixed compensation. Participants were recruited from the University of Montreal. The sample's mean age was 26.7 (SD = 4.1). Following the signature of a written informed consent form, each participant was placed in front of the computer monitor to play the game. Set on a fictitious island called Sheylan riven by drought and war, Food-Force invites participants to complete 6 virtual missions that reflect real-life obstacles faced by WFP in its emergency responses both to the tsunami and other hunger crises around the world. All participants have played only the first five missions of Food-Force. A pretest and posttest were also administered to compare learners' performance regarding the knowledge presented in the serious game. We have used 10 multiple choice questions about general problem of world hunger. Figure 3 presents a flow diagram of the experiment.

5.2. Data Collection. The motivational measurement instrument called Instructional Materials Motivation Survey (IMMS) was used following each mission to assess learners' motivational state. It is derived from four categories of ARCS motivation model. Due to time constraints and in order to achieve minimum disruption to learners, we used a short IMMS form which contained 16 out of the 32 items after receiving the advice and approval from Dr. John Keller. IMMS used a 5-point Likert-type scale (where 1 is strongly disagree and 5 is strongly agree). Furthermore, two cameras were also used to simultaneously record learners' facial expressions and game progress. Physiological data was also recorded in synchrony to both camera feeds throughout the experiment. The Galvanic Skin Resistance (GSR) electrodes and the blood volume pulse (BVP) sensor were attached to the fingers of participant's nondominant hands, leaving the other hand free for the experimental task. BVP sensor is a blood volume pulse detection sensor housed in a small finger worn package, to measure heart rate (HR). GSR electrodes measure the conductance across the skin (SC). An EEG cap was also conveniently fitted on participant's head and each cerebral sensor spot slightly filled with a saline nonsticky solution. EEG refers to the recording of the brain's spontaneous electrical activity over a period of time as recorded from multiple electrodes placed on the scalp. HR, SC, and EEG recordings were managed by the Thought Technology ProComp Infiniti Encoder [46]. This encoder has 8 protected pin sensor inputs with two channels sampled at 2048 samples per second and six channels sampled at 256 samples per second. The first two channels were used to record HR and SC. The last six other channels were used to record EEG at sites Fz, F3, C3, Pz, A1, and A2 according to the international 10–20 system. A ground is located at Fpz. Electrode impedances were maintained below 5 KΩ. Participants were asked to minimize eye blinks and muscle movements during physiological recordings. Furthermore, an additional notch filter is typically used to remove artifact caused by electrical power lines (60 Hz in Canada). According to [47], "the reference electrode should be placed in a location that is not susceptible to artifact. An extra midline electrode is suitable". Thus all EEG sites were referenced online to Cz. Electrophysiological data were recorded during the whole of the experiment. A 60s-baseline was also computed before the beginning of the game.

5.3. Data Analysis. The offline processing of the HR, SC, and EEG data was performed using BioGraph Infiniti software. EEG data were rereferenced offline to the mean of the activity at the two mastoid leads (A1 and A2). For each site $s \in \{Fz, F3, C3, Pz\}$, the corrected s is calculated using the following formula:

$$\text{corrected}_s = s - \frac{(A1 + A2)}{2}, \quad s \in \{Fz, F3, C3, Pz\}. \qquad (1)$$

Four participants (2 females) were excluded from the EEG analysis because of technical problems at the time of recording. Technical Fz recording problem with some participants leads us to exclude all Fz data from our analysis. Furthermore, manual editing of the recorded signals has been carried out to remove artifact-contaminated data caused by muscle activity and eye blinks or movements. The EEG raw signal is filtered through a band pass filter from 2 to 48 Hz. A necessary normalization technique (min-max [48]) was applied to HR and SC physiological data using the baseline data. Indeed, normalizing the data keeps the physiological patterns for individual subjects and establishes a common metric for intersubject comparisons. Min-max normalization performs a linear transformation on the original data. It has the advantage of preserving exactly all

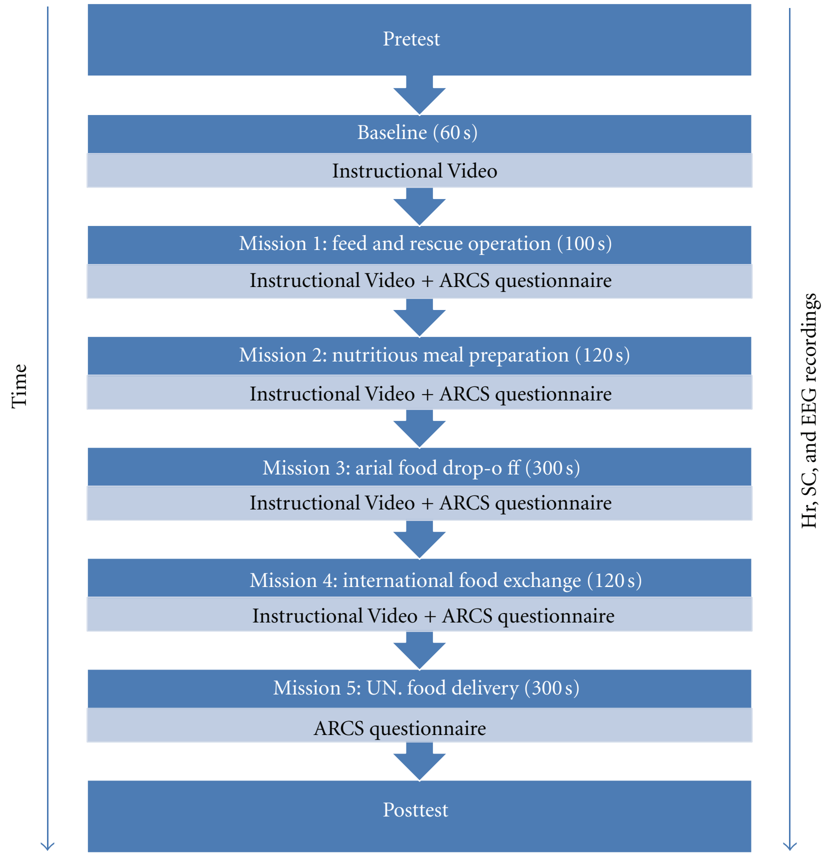


Figure 3: Progress diagram of the experiment.

relationships in the data. We have normalised each HR and SC data using the following modified formula [49]:

$$\text{normalised signal}(i) = \frac{\text{signal}(i) - \text{baseline}}{\text{signal}_{\max} - \text{signal}_{\min}}, \tag{2}$$

where $\text{signal}_{\max}$ and $\text{signal}_{\min}$ refer, respectively, to maximum and minimum values during interaction period and baseline refers to the average value of physiological data before the beginning of the game. These normalized physiological data reflect signal changes from baseline.

EEG data were segmented into one-second epochs and power spectral densities were calculated for each epoch using Fast Fourier Transformation. Power spectral data were averaged within Theta (4–8 Hz) and Low-Beta (12–20 Hz) bands. For each epoch of every participant the attention ratios (Theta/low-Beta) were calculated as described in Section 3.

5.4. Percent of Time (PoT) Index. We have defined an index representing players' physiological evolution throughout each mission of the serious game with regards to each signal signification. This index, called Percent of Time (PoT), represents the amount of time, in percent, that player's signal amplitude is lower (or higher) than a specific threshold. The PoT index is a key metric enabling us to sum up players' entire signal evolution for a mission. A simple method would be to choose the mean players' signal amplitude of each physiological sensor as the threshold. The PoT index of HR (or SC) for each player was calculated using values above the HR (or SC) threshold, whereas the PoT index for each EEG sites was calculated when player's attention ratio was below the threshold since we are looking for positive evolutions. Figure 4 illustrates an EEG attention ratio evolution during 20 seconds. The PoT for the selected 5-second window was 80% (4 values below divided by 5 values) and 70% for the entire 20 seconds (14 values below divided by 20 values).

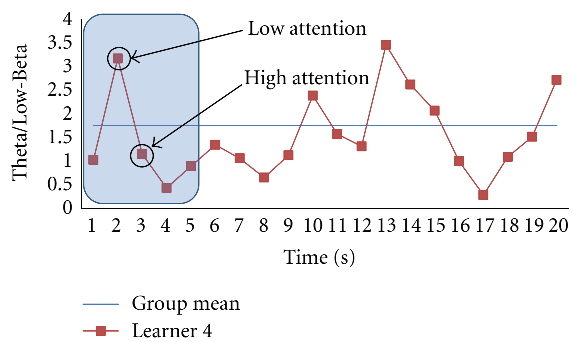


Figure 4: Learner's EEG "attention ratio" evolution.

The idea is to analyze, in a joint venture, PoT indexes of HR, SC, and EEG signals to determine, or at least estimate, relations between the motivational strategies used in the serious game and the physiological learners' responses. To that end, various AI models have been constructed using gathered data in order to classify learners in two distinct classes: "Below" and "Above". Indeed, subjects have been separated into two groups based on their self-reported scores of the ARCS model after each mission of game: those with scores below the overall average (group "Below") and those with scores above the overall average (group "Above"). For instance, the evaluation of an Attention Getting strategy (e.g., Alarm Trigger or Problem Solving) used by Food-Force will consider the *Attention* scores to determinate the "Below" and "Above" groups of subjects and compare their physiological reactions [50]. The same procedure has been applied for all other strategies. Consequently, the members of each group are different from one strategy to another. A detailed description of all these possibilities is given in the following section.

6. Experimental Results

Before presenting our results, we considered it necessary to quickly explain the statistical approach used in this section. Indeed, we could not rely on the usual parametric statistical tools such as ANOVA and t-test because (1) our sample population is small ($N = 29$ participants), (2) no justifiable assumptions could be made with regards to the normal distribution of the data, and (3) normality tests run on our data confirmed its nonnormal distribution. Hence, nonparametric Friedman's ANOVA by ranks (counterpart of the parametric one-way ANOVA) and nonparametric Wilcoxon's signed ranks test (counterpart of paired sample t-test) have been used. However, P value is interpreted in the same manner in both approaches and to that effect, reported significant P values were all computed at the 0.05 significance level (95% confidence).

6.1. Performance and Motivation. In order to determine if the IMMS scale is reliable, a Cronbach's Alpha was run on IMMS data gathered after the first mission of Food-Force. The simplified IMMS yielded reliability (Cronbach's Alpha coefficient) of 0.88 for the overall motivation measure and Cronbach's Alpha for *Attention*, *Relevance*, *Confidence*, and *Satisfaction* was 0.91, 0.71, 0.79, and 0.87, respectively. These reliability coefficients are analogous to those found in [51] and showed that the motivational measurement instrument used in the present study was highly reliable.

Since we intend to study several motivational strategies in different missions within the Food-Force game, we evaluated the effects of these strategies on learners' performance as well as their motivation. We have then conducted statistical tests and we have obtained several results regarding knowledge acquisition (pre- and posttests) and learners' motivation (ARCS scores). The results of Wilcoxon signed ranks test displayed in Table 1 showed a significant difference between the participants' scores of the pre- and posttests in terms of knowledge acquisition ($Z = 4.65$, $P < 0.001$). Number of correct answers after finishing the game is significantly higher than that of correct answers before start playing. The results of Friedman's ANOVA by ranks between ARCS scores are displayed in Table 2. Significant differences for the general motivational scores as well as each category of the ARCS model were also observed between missions, except for *Relevance* (motivation overall score: $F(1,4) = 10.16$, $P < 0.05$; *Attention*: $F(1,4) = 19.51$, $P < 0.001$; *Relevance*: $F(1,4) = 7.38$, $P = 0.12$; *Confidence*: $F(1,4) = 16.8$, $P < 0.05$; *Satisfaction*: $F(1,4) = 10.85$, $P < 0.05$). Nonsignificant results of the Relevance category can be explained by the fact that the Relevance Producing strategy (Instructional Video) presented between missions was roughly the same: video segments explain the goal of each mission or its real application in order to connect each mission to the problem of world hunger. Conversely, the *Attention* category which showed the strongest difference and rank has used various game strategies throughout the missions. Indeed, Food-Force maintains learners' attention by using Alarm Trigger when they are confronted with an unexpected situation such as attacks to the convoy by local rebel forces or flat tires of trucks (mission 5). It also includes mental tasks that require concentration and attention: drop food from the air without risking human lives (mission 3) and guide a convoy of trucks safely to a feeding centre while overcoming challenges from clearing land mines to rebuilding bridges and negotiating with local rebel forces (mission 5). Finally, learners' attention is possibly gained by using Problem Solving strategy such as finding the right combination of different food items (rice, beans, vegetable oil, sugar, and iodized salt) to create a nutritious and balanced diet, all at a target cost of 30 US cents per person per meal (mission 2).

Table 1: Results of Wilcoxon signed ranks test.

Test	Mean	Median	SD	Z	Sig. P
Pretest	6,07	6	1,387	4,657	.000*
Posttest	8,86	9	.990		

* Significance at the .05 level.

An example of an Alarm Trigger used in mission 5 is shown in Figure 2. As described in Section 4, Alarm Trigger is a motivational strategy (Attention Getting strategy) associated to *Attention* category of the ARCS model. We have then considered self-reported Attention scores to separate participants into two groups: a "Below" class (4 females and 7 males) representing participants who reported an *Attention* score below that of the overall mean and an "Above" class (5 females and 13 males) presenting the opposite (a score above the overall mean). Three alarms in mission 5 have been investigated. They are a sound trigger followed by Food-Force logistics officer's comments used to help players to overcome challenges—from clearing land mines to rebuilding bridges and negotiating with local rebel forces. To detect physiological changes for each player, we considered two 5-second windows computed before and after each alarm and calculated their means ($\text{mean}_{\text{Before Alarm}}$, $\text{mean}_{\text{After Alarm}}$). Fifteen Wilcoxon signed ranks tests (3 alarms $\times$ 5 physiological sensors) were run between Before Alarm and After Alarm data and significant results were

Table 2: Results of Friedman's ANOVA by ranks.

(a)

Motivation	Mean	Median	SD	Chi-Square	Sig. *P*
Mission 1	55,14	55	10,347		
Mission 2	54,66	55	11,321		
Mission 3	52,00	50	11,206	4,657	.000*
Mission 4	58,93	62	10,535		
Mission 5	56,45	54	10,377		

* Significance at the .001 level.

(b)

Attention	Mean	Median	SD	Chi-Square	Sig. *P*
Mission 1	14,334	15	3,351		
Mission 2	16,310	18	3,883		
Mission 3	16,000	17	3,595	19,512	.001*
Mission 4	16,862	17	3,090		
Mission 5	17,620	19	3,121		

* Significance at the .01 level.

(c)

Relevance	Mean	Median	SD	Chi-Square	Sig. *P*
Mission 1	12,689	14	5,745		
Mission 2	11,000	9	5,855		
Mission 3	9,482	7	5,369	7,379	.117
Mission 4	12,620	12	5,747		
Mission 5	10,758	10	4,852		

* Significance at the .05 level.

(d)

Confidence	Mean	Median	SD	Chi-Square	Sig. *P*
Mission 1	14,689	16	4,629		
Mission 2	12,655	14	4,760		
Mission 3	11,241	12	4,725	16,833	.002*
Mission 4	14,586	16	4,452		
Mission 5	12,344	14	4,466		

* Significance at the .01 level.

(e)

Satisfaction	Mean	Median	SD	Chi-Square	Sig. *P*
Mission 1	13,413	14	2,872		
Mission 2	14,689	15	3,495		
Mission 3	15,275	16	3,463	10,852	.028*
Mission 4	14,862	15	2,812		
Mission 5	15,724	15	2,986		

* Significance at the .05 level.

obtained for all data. The 3 Alarms Triggers and learners' physiological trends are presented in Figure 5. Each dot on the graph represents the difference between the two means for each alarm ($\text{mean}_{\text{After Alarm}} - \text{mean}_{\text{Before Alarm}}$). Figure 5 shows almost complete opposite trends for all physiological data between the "Below" and "Above" classes, *except* for SC. The physiological analysis pointed towards the fact that the "effect" of an Alarm Trigger seems to decrease over time. We can see on Figure 5(a) that the effect of those alarms on SC seems to slowly fade after the second alarm, contrary to the popular belief. Indeed, one may think that intervening with color and sound tends to capture learners attention, but our findings seem to indicate that this is only partially true. There seems to be a certain "adaptation" on the part of the learner with regards to SC at the very least. Nevertheless, any permanent diagnosis regarding learners' attention level in reaction to an Alarm Trigger based only on SC at this point may be hasty or even wrong for there are numerous other

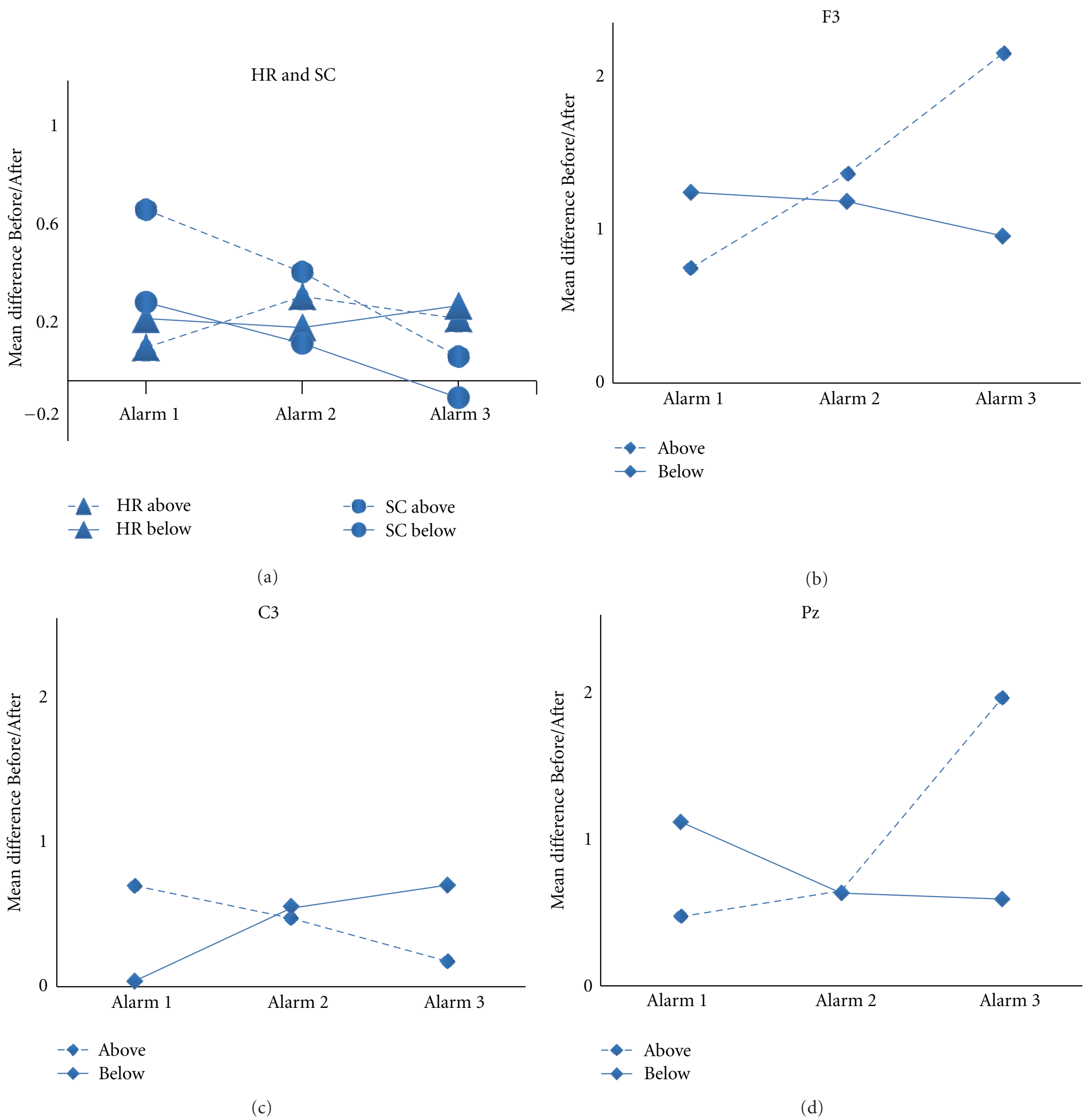
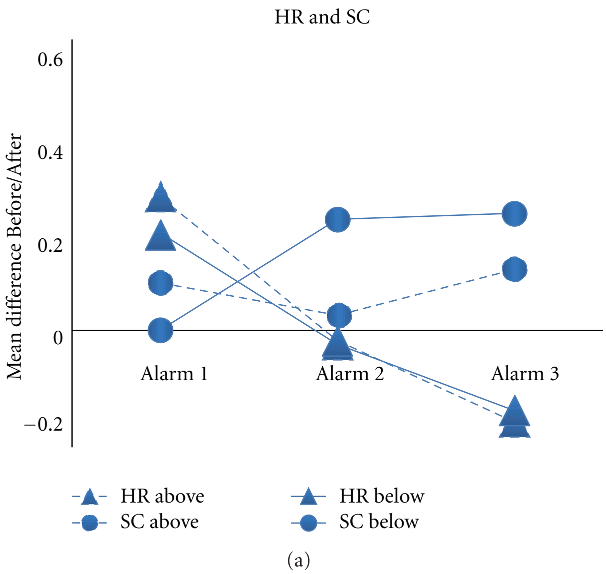


Figure 5: HR, SC, and EEG trends for three Alarm Triggers (mission 5 of Food-Force): each dot in all subfigures shows the difference between $\text{Mean}_{\text{After Alarm}}$ and $\text{Mean}_{\text{Before Alarm}}$ physiological data.

physiological trends to consider first. Indeed, even if no clear trends were found in HR, the cerebral data provided clarity in distinguishing between the two classes.

In fact, variations in the attention ratio are clearly evident for both classes. We found numerous occasions when two participants from different classes had the same SC and HR trends but have shown very opposite trends in EEG sites, especially C3 area. An example of this situation is illustrated in Figure 6: two participants had the same HR and SC trends but only an opposite trend in C3 helped us identify their respective attention classes. These results seem to show the relevance and importance of adding the EEG in assessing learners' attention change, even more so when this change cannot be clearly established by the use of HR and SC alone. Thus, the EEG "attention ratio" generally increases for participants who reported a *low Attention* category score (class "Below") whereas the same ratio decreases for the learners in the class "Above".

6.2. Logistic Regression Analysis. Subjects have been separated into two groups according to their ARCS scores after each mission: those with scores below the overall average (group "Below") and those with scores above the overall average (group "Above"). We have run logistic regressions



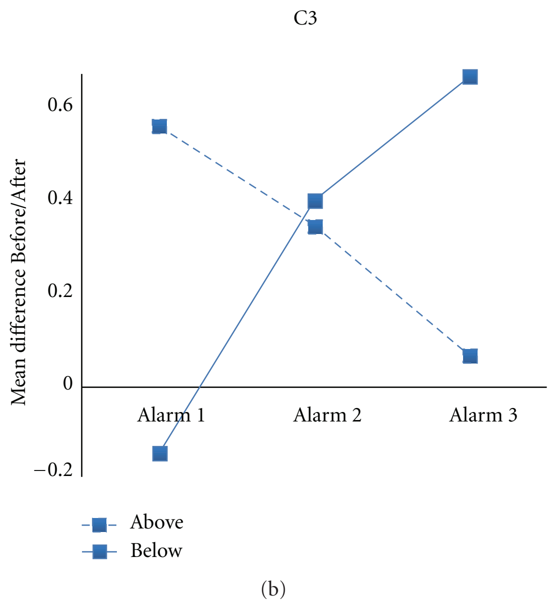


Figure 6: Comparison of physiological trends of 2 learners in 2 different classes: the same HR and SC trends (a) and opposite C3 mean difference Before/After trends (b).

Table 3: Omnibus tests of model coefficients (logistic regression).

Strategy	Chi-Square	df	Sig.	Nagelkerke R^2
Problem Solving	15,893	5	.007*	.574
Alarm Trigger	18,706	5	.002*	.647
Instructional Video	7,563	5	.182	.312
Informative Feedback	15,468	5	.009*	.563
Explanatory Feedback	12,103	5	.033*	.464
Displaying Score	11,974	5	.035*	.460

* Significance at the .05 level.

to predict learners' group ("Above" or "Below") for each studied strategy. The dependent variable in logistic regression is usually dichotomous, that is, the "Above" group coded as "1" whereas the "Below" group coded as "0". Furthermore, logistic regression makes no assumption about the distribution of the independent variables. These variables do not have to be normally distributed, linearly related or of equal variance within each group. Our prediction models used all computed PoT indexes as predictor variables (PoT-SC, PoT-HR, PoT-F3, PoT-C3, and PoT-Pz) and the Enter method for variable selection. Table 3 reports the results of adding five predictors (df = 5) to the regression model. Results indicated that adding predictors to the model has significantly increased our ability to distinguish between "Above" and "Below" groups for all studied motivational strategies, except for Instructional Video (see Table 3: Chi-Square and Sig. values with conventional significance level of 0.05). In addition, Nagelkerke's R^2 values of Table 3 ranged from 46% to 65% and indicated a moderately high relationship between the predictors and the dependent variable. Table 5 showed the classification tables which tell us how many of the cases where the observed values of the dependent variable were 1 or 0, respectively have been correctly predicted. In each classification table, the columns are the two predicted values of the dependent, while the rows are the two observed values of the dependent. Prediction success overall was between 65.5% and 79.3% (see Table 5). The Wald criterion demonstrated that PoT-C3 especially made a significant contribution to prediction (see Table 4). Other variables were not significant predictors. Results of regression models clearly showed that physiological data, especially EEG "attention ratio", were relevant to evaluate motivational strategies. The most significant differences between groups were shown for *Attention Getting Strategies* though. One reason may be the limitation of the "attention ratio" (Theta/low-Beta) which seems to be inappropriate to identify EEG patterns other than those correlated with the *Attention* category. Regarding the physiological analysis, it is preferable to explore alternative EEG frequency ratios based on additional brainwaves such as Alpha (8–12 Hz) and High-Beta (20–32 Hz) in order to highlight other patterns correlated with learner's motivation. Furthermore, F3 and C3 areas showed more significant differences of PoT trends than Pz area which showed roughly similar trends between groups. This is can be explained by specific functions associated with the middle parietal (Pz) area. These functions

Table 4: Tables of variables in the equation (logistic regression).

	B	SE	Wald	df	Sig.	Exp(B)
Problem Solving						
PoT-HR	−.072	1,246	.003	1	.954	.931
PoT-SC	.733	.958	.586	1	.444	2,082
PoT-F3	.271	.681	.159	1	.691	1,312
PoT-C3	−3,473	1,580	4,829	1	.028*	.031
PoT-Pz	−.039	1,075	.001	1	.971	.961
Constant	3,995	2,359	2,867	1	.090	54,335
Alarm Trigger						
PoT-HR	−1,733	1,210	2,053	1	.152	.177
PoT-SC	1,990	1,459	1,861	1	.173	7,314
PoT-F3	.785	.802	.960	1	.327	2,193
PoT-C3	−4,462	1,890	5,576	1	.018*	.012
PoT-Pz	.282	1,263	.050	1	.823	1,326
Constant	4,733	2,430	3,795	1	.051	113,643
Instructional Video						
PoT-HR	−.618	.684	.815	1	.367	.539
PoT-SC	.879	.729	1,455	1	.228	2,408
PoT-F3	.462	.471	.960	1	.327	1,587
PoT-C3	−.914	.565	2,620	1	.106	.401
PoT-Pz	−.378	.790	.229	1	.633	.685
Constant	1,150	1,283	.804	1	.370	3,160
Explanatory Feedback						
PoT-HR	−.828	.919	.812	1	.368	.437
PoT-SC	1,523	1,134	1,804	1	.179	4,588
PoT-F3	−.102	.637	.026	1	.873	.903
PoT-C3	−1,969	1,180	2,784	1	.095	.140
PoT-Pz	−.717	1,099	.426	1	.514	.488
Constant	3,237	1,749	3,426	1	.064	25,452
Informative Feedback						
PoT-HR	.950	.789	1,450	1	.229	2,585
PoT-SC	1,795	.997	3,241	1	.072	6,018
PoT-F3	−1,872	.938	3,978	1	.046	.154
PoT-C3	2,084	.868	5,759	1	.016*	8,033
PoT-Pz	−.316	.605	.272	1	.602	.729
Constant	−1,848	1,354	1,864	1	.172	.158
Displaying Score						
PoT-HR	.806	.953	.716	1	.398	2,239
PoT-SC	.478	1,001	.227	1	.633	1,612
PoT-F3	−.068	.526	.017	1	.897	.934
PoT-C3	−1,149	.534	4,635	1	.031*	.317
PoT-Pz	−1,221	.784	2,424	1	.119	.295
Constant	2,074	1,457	2,027	1	.155	7,957

* Significance at the .05 level.

incorporate appreciation of form, sensory combination and comprehension (pain, pressure, heat, cold, and touch) which are quite sparse or even absent in all missions. Learners tended to rely mostly on the frontal cortex (F3) because it is known to be strongly implicated in taking quick decisions under pressure. The central region of the brain (C3) seems to be the most solicited when a more “generalized” problem solving approach is used. Not only our results show that physiological data can provide an objective evaluation of motivational strategies for clearly distinguishing between learners’ reactions, but also the relevance and importance of adding the EEG in our empirical study. The obtained

Table 5: Classification tables (logistic regression).

Observed	Predicted		
	Below	Above	Percentage correct
Problem Solving			
Below	7	4	63,6
Above	2	16	88,8
Overall percentage			79,3
Alarm Trigger			
Below	8	3	72,7
Above	4	14	77,7
Overall percentage			75,8
Instructional Video			
Below	10	6	62,5
Above	4	9	69,2
Overall percentage			65,5
Explanatory Feedback			
Below	8	2	80
Above	4	15	78,9
Overall percentage			79,3
Informative Feedback			
Below	7	3	70
Above	4	15	78,9
Overall percentage			75,8
Displaying Score			
Below	6	2	75
Above	4	17	80,9
Overall percentage			79,3

results also open the door to the possibility to evaluate other motivational strategies used in different intelligent systems.

7. Conclusion and Future Work

In this paper, we have assessed the effects of some motivational strategies in Food-Force on learners' motivation using the ARCS theoretical model as well as three physiological sensors: HR, SC, and EEG. We have successfully answered our first research question by identifying physiological patterns, especially EEG Theta/low-Beta ratio, to evaluate motivational strategies. We then successfully answered our second research question by using these physiological trends to build prediction models of learners' motivation. These models were able to moderately distinguish motivating strategies from those with low impacts on learners' motivation. Our findings showed that SC and HR may reach their limits in some cases for evaluating the impacts of motivational strategies on learners. In fact, no clear trends were found in SC and HR for evaluating some studied strategies. However, C3 Theta/low-Beta ratio has showed different trends between groups for almost all studied strategies. It can give valuable evaluation of motivational strategies.

Statistical and physiological study of our data has given some insights into the assessment of learners' motivation during playing a serious game. It has shown that physiological parameters are suitable to assess the effects of motivational strategies on learners' motivation. The obtained results are very encouraging to an ITS because (1) it is possible to assess the effects of tutor's interventions on learners' motivation, (2) we can rely on this assessment as a substitute for self-reports that can disrupt a learning session, and (3) it is possible to enrich the Learner Model (which describes learners' behaviors and evaluates their knowledge) with a motivational component based on our results, thus enabling the Tutor Model (which uses the Learner Model and customizes learning environments by adapting learning strategies in order to respond intelligently to learners' needs, objectives, and interests) to properly adapt its interventions.

However, one limitation in this work is the assumption that the ARCS categories are independent from each other. Simultaneous strategies in SG can be related to different categories of the ARCS model. One possible extension of the present work would be to consider dependencies between ARCS categories. In addition, we can extend the present work to study more than two classes of motivation. Multinomial logistic regression will be used in this case in counterpart of binary logistic regression. It is also possible to add other variables that can improve the prediction quality of our models. Indeed, some personals characteristics (age, gender, player style, hours spent playing video games, etc.) can be additional predictors for players' motivation. Furthermore, brain activity can also be better analysed in the future and other EEG analysis methods, such as the event-related potential (ERP) technique, can be used to test whether different events in serious game evoke differential EEG responses. We plan, therefore, to address all these possibilities in a further complementary study.

Conflict of Interests

The authors declare that they have no conflict of interests in the research.

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