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Article information:

To cite this document:

Boyan Bontchev, Dessislava Vassileva, (2017) "Affect-based adaptation of an applied video game for educational purposes", Interactive Technology and Smart Education, Vol. 14 Issue: 1, pp.31-49,

<https://doi.org/10.1108/ITSE-07-2016-0023>

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Affect-based adaptation of an applied video game for educational purposes

Video game for
educational
purposes

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Received 20 July 2016
Revised 6 December 2016
22 December 2016
Accepted 10 January 2017

Abstract

Purpose – This paper aims to clarify how affect-based adaptation can improve implicit recognition of playing style of individuals during game sessions. This study presents the “Rush for Gold” game using dynamic difficulty adjustment of tasks based on both player performance and affectation inferred through electrodermal activity and facial expressions of the player. The game applies linear regression for calculating playing styles to be applied for achieving a style-based adaptation in other educational video games.

Design/methodology/approach – The experimental procedure included subject selection, demonstration, informed consent procedure, two game sessions in random order – one without and another with affective adaptation control – and post-game self-report. The experiment was conducted with participation of 30 master students and university lecturers in informatics.

Findings – This study presents experimental results concerning the impact of affective adaptation over playing style recognition, game session time, task's effectiveness, efficiency and difficulty and, as well, player's assessment of affectively adaptive gameplay obtained by an adaptation control panel embedded into the game and by post-game self-report.

Research limitations/implications – The proposed adaptive game limits recognised styles to such based on the Kolb's Learning Style Inventory model. Another limitation of the study is the relatively small number of participants constrained by the extended experimental procedure and the desktop game version.

Originality/value – The paper presents an original research on the effect of affect-based adaptation on a novel approach for implicit recognition of playing styles.

Keywords Adaptation, Game-based learning, Affective, Applied games, Playing styles

Paper type Research paper

1. Introduction

In past decades, the interest towards computer games applied for education increased thanks to their positive outcomes and effects in e-learning (Coller and Scott, 2009). Modern video games are able to retain the learning interest of players during the game session by providing an intriguing and highly immersive gameplay. The most significant effect on the achievement of immersion in video games is accomplished by keeping a balance between



The research leading to these results has received funding from the People Programme (Marie Curie Actions) of the European Union's 7th Framework Programme FP7/2007-2013/project ADAPTIVES (ADAPTive player-centric serious video gaMES) under REA Grant agreement no. 624184 and, as well, from the EC H2020 project RAGE (Realising an Applied Gaming Eco-System), Grant agreement no. 644187.

Interactive Technology and Smart
Education
Vol. 14 No. 1, 2017
pp. 31-49
© Emerald Publishing Limited
1741-5659
DOI 10.1108/ITSE-07-2016-0023

challenges and skills (Nogueira *et al.*, 2013). There were found very promising results concerning adaptive educational games adjusting their features such as task difficulty, object speed and learning content according to the current state of the player (Brisson *et al.*, 2012; Chang, 2013) and, as well, to his/her playing style (Magerko *et al.*, 2008; Wong *et al.*, 2009; Lindberg and Laine, 2016).

Players have a predominantly emotional than rational personality. Therefore, tailoring gameplay to player's emotions is crucially important for assuring optimal experience causing high immersion and commitment during the game, that is, for keeping players in flow (Sweetser and Wyeth, 2005). By means of controlling player's emotional state by the game, game developers are able to increase player's attention, interest and sense of satisfaction. Game researchers apply various techniques for recognition of human emotions, such as the analysis of players' responses, self-reports, emotional inference based on facial and/or gesture expressions and measurement of changes in player's psychophysiological state (Kivikangas *et al.*, 2011). In this way, a video game can be adjusted to the affective state of the player, that is, player's emotions and arousal can be used for tailoring mechanics, dynamics and aesthetics of the game. Affect-based adaptation of applied video games may lead to an increased immersion of the player and, as well, to improved interactions between the player and the game (Fairclough and Gilleade, 2012). In educational games, adjustment based on player's affect can improve the learning process, students' attention to content and didactic activities and learning outcomes (Brisson *et al.*, 2012; Yannakakis and Paiva, 2014).

In this article, we report some findings from a study that explored how psycho-emotional processes and playing style can be used as a basis for efficient player-centric adaptation in applied games (Bontchev, 2016). We were interested, on one hand, in finding the effect of affective adaptation on various gameplay metrics and on the way the player does assess it and, on the other hand, in evaluating its impact on the accuracy of implicit, in-game recognition of playing styles. More precisely, this implies answering three main research questions, as follows:

- RQ1. What are the benefits of affective adaptation of gameplay over effectiveness, efficiency and achieved difficulty of execution of tasks of various types within an applied game?
- RQ2. What is the impact of affectively adaptive gameplay over accuracy of implicit recognition of playing styles (PS) during the game session?
- RQ3. What is the assessment of affective adaptation reported by the player during the game session, and how is it correlated with post-game self-report?

For answering these questions by a practical experiment, adaptation based on recognition of player's emotions and arousal was applied for improving a video game for educational purposes named "Rush for Gold". The goal of this affectively adaptive game is to recognise implicitly the playing style of the person during the game, without the player to be aware of it. After validating the recognition of playing style by means of self-reports, the calculated style was used for adaptation of game content within an educational maze game. For the recognition of playing and learning style of an individual player with higher accuracy, adjustment of game dynamics and aesthetics is applied. Affect-based adaptation of gameplay was introduced into the game with the hypothesis that it will result in a shorter playing time and better efficiency and difficulty of completed tasks compared to the non-adaptive gameplay. For this reason, the adaptive version of the "Rush for Gold" game applies means for player affect recognition based on electrodermal activity (EDA) used for arousal detection and facial expressions for inference of the six basic emotions. An

experiment related to the effect of affective adaptation of dynamic difficulty adjustment (DDA) on recognition of PS was conducted with participation of 30 master students and university lecturers, who played the adaptive game and reported both their playing style and evaluation of the game. The received results allow us to conclude that adaptive gameplay leads to shorter playing time and better efficiency and difficulty compared to the non-adaptive one and, as expected, to an improved recognition of PS with higher accuracy. Therefore, recognised playing style can be successfully applied for achieving a style-based adaptation in other educational video games.

2. Related works

2.1 Adaptive games using player affect

Both entertainment and applied video games are organised around “a functional epistemology, where one learns through doing, through performance” (Squire, 2006). This unique characteristic of video games opens the door for adaptation methods based on player’s performance for fostering intrinsic and extrinsic learning motivations of the player (Magerko *et al.*, 2008) while increasing enjoyment of playing (Sweetser and Wyeth, 2005). Next to performance, player’s emotions provide a fundament for affect-based adjustment of game feature, though staying restricted to laboratory experiments (Kivikangas *et al.*, 2011). For an effective implementation of emotional game adaptation, applied affective loop should meet four criteria for sufficient sensibility and reliability (Fairclough and Gilleade, 2012):

- (1) The loop should react on player affectation in a predictable way.
- (2) The psychophysiological measures have to reflect adequately the emotional state of the player.
- (3) Classification of emotions should assure both high accuracy and recall.
- (4) The adaptation control has to adjust game features for inducing an adequate effect on the player.

Various experiments with emotion-based games proved that dynamic adaption of specific game features tailored either according to recognised emotions or directly to measured physiological signals improves player’s engagement, immersion and challenge (Yannakakis and Paiva, 2014). DDA is the most popular method for dynamic control of task’s difficulty by using a positive feedback loop (Chang, 2013). Usually, affect-based adaptation applies DDA based on player emotions recognised either by facial expressions and/or by psychophysiological measurements.

2.2 Measuring arousal by means of electrodermal activity

EDA is the most popular and affordable psychophysiological measure of skin conductance. EDA is a characteristic that is independent of parasympathetic responses and its changes are a result of activity of the sympathetic branch of the autonomic nervous system (Braithwaite *et al.*, 2015). Changes of EDA could be triggered by emotional and cognitive stimuli as well as by motor processes (Charney *et al.*, 2013). Because eccrine sweat glands correlate closely with EDA, usually EDA is measured by two electrodes attached to the fingers or to the palm of the hand. EDA contains two main components – tonic and phasic (Boucsein, 2011). The tonic component refers to the emotional background of an individual and is characterised with slow climbing and small deviations from the overall degree of arousal. The phasic component reflects recent changes in the emotional state that are provoked from external stimuli. There are two main methods for electrodermal recordings – *endosomatic* (when external current is not used) and *exosomatic* (when it is either direct current or alternating current). The later one is more frequently used by researchers (Braithwaite *et al.*, 2015) for

measuring the tonic level by means of skin conductance level (SCL) and phasic response through skin conductance response (SCR). The interval of possible values for SCL ranges from 2 to 20 microsiemens (μS), and SCR may vary from 0.02 to 5 μS , whereupon electrodermal measures can be different for each individual (Charney *et al.*, 2013). Usually, denoising filters and Butterworth filters (Braithwaite *et al.*, 2015) are applied to the EDA signal to eliminate noise and to achieve separation between tonic and phasic components, respectively. Recent studies show that both tonic and phasic components are important for identifying the level of emotional arousal (Bach *et al.*, 2010). For better accuracy and reliability in inferring arousal, some authors recommend sample rate to be at least 100-200 Hz (Figner and Murphy, 2011).

2.3 Emotion recognition based on facial expressions

Researchers apply various methods for emotion recognition based on voice intonation, gestures and facial expressions. In this paper, we focus on methods using facial expressions as being most appropriate for any type of game. First, Paul Ekman identified six universal emotions – happiness, sadness, surprise, fear, anger and disgust – that are culturally, geographically and ethnically independent (Ekman and Friesen, 1971). Later, Ekman and Friesen (1978) proposed the Facial Action Coding System that is one of the most used tools for measuring facial expressions. Research studies on automatic facial expression recognition started in the beginning of nineties with appearing of high-resolution cameras and increasing the computational power of the computer processors (Cohen *et al.*, 2000). Thus, results from the works of Ekman and Friesen were used in algorithms for automatic emotion detection from facial expressions in images or video (Yacoub and Davis, 1996).

Main problems with modern emotion recognition systems are related to different types of illumination, occlusions and performance issues, and some of them have problems with applying techniques for defining face colour, texture and furrows (Beristain and Graña, 2009). Moreover, inferring human emotions based on facial expression may be problematic when emotions are intentionally expressed, exaggerated or suppressed during the observation (Jack *et al.*, 2014). Therefore, emotion recognition based on facial expressions should not be applied in isolation but together with other methods such as self-reports or physiological measurements.

2.4 Measuring and recognition of learning and playing styles

Both learning and playing styles are recognised as important foundations for creating style-based adaptation of educational games. Learning styles (LS) are a subject of many psychological and pedagogical studies for decades and concern “characteristic cognitive, effective, and psychosocial behaviours that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment” (Curry, 1981). Two of the most popular models and measuring instruments of LS are the Learning Style Inventory proposed by Kolb (1984) (*accommodator, diverger, converger and assimilator*) and the Learning Style Questionnaire of Honey and Mumford (1992) built on top of Kolb’s model and including four distinct types of learners: *activists* (learning mainly by experience), *reflectors* (learning presumably from reflective observations), *theorists* (learning from exploring interrelationships) and *pragmatists* (learning from acting with practical outcomes).

PS represent persistent traits of the player, with treating “motivations as a more temporary state, with an implication that players may adopt different play styles in different games or at different times” (Magerko *et al.*, 2008). The Bartle’s player types model (Bartle, 1996) was created for multiplayer games and comprises four player types: *killers*, *achievers*, *explorers* and *socialisers*. The Demographic Game Design Model proposed by Bateman and

Boon (Bateman *et al.*, 2011) defined four player styles: *wanderers* (enjoying new experiences and discovering), *conquerors* (looking for overcoming game challenges), *managers* (mastering the game in details) and *participants* (enjoying social interaction). The ADOPTA playing style model was conceived especially for educational games on top of the Kolb's Learning Style Inventory (Aleksieva-Petrova *et al.*, 2011) defining four PS within the perception continuum (feeling versus thinking) and processing continuum (watching versus doing): *competitors* (motto: *feel and do*), *dreamers* (motto: *feel and watch*), *logicians* (motto: *watch and think*) and *strategists* (motto: *think and do*). A questionnaire containing 40 binary choice items about the ADOPTA playing style was designed and proven for having good validity and rest–retest reliability (Bontchev, 2016). ADOPTA PS appeared to be highly correlated to LS of Honey and Mumford (average $r = 0.75261$, $p < 0.0000$ for $N = 152$), because both the style families are based on the Kolb Learning Style Inventory.

Measuring and recognition of both LS and PS are of crucial importance for adaptation of educational games. Assessment of styles based on self-reports implies administering of long questionnaires, which can be boring for players. On the other hand, players are asked about their styles before or after the game session, which might introduce bias in the results. Therefore, implicit recognition of PS appears to be a more ecological and effective instrument, especially when incorporated into the game.

Up to present, few studies have attempted to recognise PS by gameplay metrics. Wong *et al.* (2009) applied a self-organising map to categorise similar behavioural data gathered from each player in real time. By means of unsupervised clustering, players' data were grouped within a style-based player model used for non-invasive game adaptation. Etheredge *et al.* (2013) used fuzzy cluster analysis and a hidden Markov model for classifying automatically players' behaviour in games of any type. However, these methods are rather generic, because they are focused neither on a specific family of PS nor on a given type of game. Hence, applying such methods of automated style recognition for controlling adaptation in games is questionable.

3. Adaptive game design

"Rush for Gold" was specially conceived as an action video game aiming at implicit recognition of PS using player metrics, intended to be used further for style-based adaptation of educational maze games (Bontchev, 2015). Affect-based adaptation of gameplay was introduced into the game with the hypothesis that it will result in shorter playing time and better efficiency and higher difficulty of completed tasks compared to the non-adaptive gameplay. Answering this research question appears to be the main goal of this study.

3.1 Game tasks for playing style recognition

"Rush for Gold" recognises implicitly the ADOPTA playing style of an individual learner by tracking his/her behaviour during accomplishment of specific game tasks and applying collected player's metric in linear regression formulas for calculation of each playing style (Bontchev and Vassileva, 2016). Linear regression coefficients were determined first by structured interviews with game-based learning practitioners and, next, were corrected by the least squares method using self-report results for validation. Linear regression calculations of competitor, dreamer and logician playing style use player effectiveness (i.e. result), achieved efficiency (as ratio between achieved result and effort done) and difficulty of accomplishing a task specific to this style. For calculation of strategist playing style, the game applies relative time for solving a task, average efficiency (AE) achieved in performing various tasks, average relative difficulty, number of planning events, number of plan monitoring events and average relative effort for performing all types of explicit tasks.

The game comprises three types of explicit tasks concerning collection of 12 gold bars in an Egyptian temple and challenging player’s knowledge and intellectual abilities including synthetic, analytical and practical skills, as follows:

- (1) *Group A – shooting tasks*: The player has to hit and collect between two and six bars of gold (bullions) flying near the ceiling of the temple (Figure 1) by shooting at appropriate position and, next, by pressing on the fallen bar of gold to collect it.
- (2) *Group B – discovering tasks*: The player has to discover and collect between two and six gold bullions hidden in secret places at the temple.
- (3) *Group C – puzzle-solving tasks*: The player has to solve between two and six of the logic puzzles shown at the pedestals of statues at the temple (for example, left in Figure 1); a correct answer makes a bullion to appear over the pedestal and the player can collect it by a mouse click.

Besides the explicit game-driven tasks, “Rush for Gold” includes also some implicit tasks not expressly stated in the game, but expected to be fulfilled, such as maximising skills in shooting, discovering and solving, or how to explore the temple when changing visual properties or doing strategic planning and monitoring of playing activities. For the final implicit task, a Strategy Management Table (SMT) is supported representing a table with three rows for planning number of gold bars of Groups A, B and C, whereupon their total number should equal to 12. In addition, SMT provides data about AE of performance of tasks of each group formed, as follows:

- *Group A*: AE is calculated as the number of hit bullions divided by the total number of shots.
- *Group B*: AE is the number of found bullions divided by the number of passes near hidden bullions until finding and collecting them.
- *Group B*: AE equals to the number of right answers divided by the total number of answers tried by the player.



Figure 1.
A view of the “Rush
for Gold” temple

If no SMT planning is introduced by the player, then each successfully collected bar of gold of given group provokes appearance of a new bullion of the same group until reaching the allowed maximum of bullions. After collecting all the 12 gold bars, or at any moment by pressing the FINISH button, the game estimates the PS by applying linear regressions as explained above, writes them down to a log file together with all other session data and shows the styles to the player.

3.2 Adaptable game features

To achieve an improved, player-centric gameplay together with a higher effectiveness and efficiency of task accomplishment, “Rush for Gold” introduces two ways for gameplay adaptation – the first based on player’s performance (Squire, 2006) and the second according to player’s affect (Kivikangas *et al.*, 2011).

3.2.1 Gameplay adaptation based on player’s performance. As Brisson *et al.* (2012) stated, a digital game “should adapt to a players competency levels”, whereupon “users are likely to express a wide range of cognitive and motor skills affecting both their preferences and performances during game-play”. In the “Rush for Gold” game, performance-based adaptation of gameplay is applied for dynamic adjustment of task difficulty for the gold bars shooting and discovering and puzzle-solving tasks. Tasks of these three types start with difficulty level equal to 1. After successful task completion, difficulty of next task increases if the last achieved efficiency is equal or greater than 50 per cent for shooting and puzzle-solving tasks and 67 per cent for discovering tasks, as presented in Table I. If the last achieved efficiency is equal or less than 25 per cent for shooting and puzzle-solving tasks and 33 per cent for discovering tasks, next task difficulty will be decreased. In any other cases, next task difficulty remains the same. Thus, the level of difficulty is adjusted between 1 (minimum) and 3 (maximum).

The shooting difficulty is adapted by means of two parameters:

- (1) defeat range of shooting (higher difficulty means smaller defeat range); and
- (2) velocity of flying gold bars (higher difficulty means higher velocity).

Discovering difficulty is adjusted by hiding the gold bars in more hidden and difficult places, and efficiency is computed as a function of the number of passes near hidden items until finding them. On the other hand, difficulty of logic puzzles is predefined and cannot be changed according to some player’s metric because sudden replacement of the puzzle before being solved would disturb the players. Therefore, performance-based adaptation of puzzle tasks applies choosing the next puzzle with difficulty according to the logic explained over, without changing it until being solved.

3.2.2 Gameplay adaptation based on player affect. Affect-based game adaptation adjusts some game features according to induced emotions and is applied to create more dynamic and immersive gameplay moving players to desired emotional state and resulting in situated

Type of task	Last task execution efficiency (E)	Task difficulty
Shooting or solving tasks	$E \geq 0.5$	Incremented
Shooting or solving tasks	$0.25 < E < 0.5$	Not changed
Shooting or solving tasks	$E \geq 0.25$	Decrement
Discovering tasks	$E \geq 0.67$	Incremented
Discovering tasks	$0.33 < E < 0.67$	Not changed
Discovering tasks	$E \leq 0.33$	Decrement

Table I.
Adjustment of task
difficulties based on
player’s performance

game experiences (Sweetser and Wyeth, 2005). The “Rush for Gold” video game applies a positive affective feedback loop for dynamic tailoring of difficulty of three types of tasks and, as well, for adjusting ambient light intensity. Dynamic level content adjustment (Chang, 2013) was applied for tailoring activities with game items, such as shooting and discovering tasks. According to player’s skills shown during task execution, it adapts dynamically the level of task difficulty applying specific threshold values. In this way, hidden bars of gold turn to be more difficult to be discovered with the increase of player’s positive emotions or arousal. Similarly, flying bullions change their velocity and acceleration (set initially according to player’s performance), when affectation level becomes higher. In contrast to shooting and discovering tasks, puzzle-solving tasks are not suitable for dynamic affect-based adaptation, because DDA of a shown puzzle would suddenly replace it by another one having different difficulty, while the player tries to solve it. For this reason, puzzle-solving tasks apply affect-based adaptation statically, at the moment of selection of the next puzzle.

Besides DDA of shooting and discovering tasks plus static adaptation of puzzle difficulty, the game introduces dynamic affective adaptation of visual effects. According to player’s emotions and arousal levels, ambient light intensity is adapted using specific thresholds. Table II presents applied dynamic adjustment of difficulty of tasks and illumination (light intensity) according to player’s affectation level (comprising emotions or arousal). All these adjustments are valid for positive affective feedback loop, which is default for the game. However, “Rush for Gold” allows the player to change both the direction and strength of the affective feedback loop.

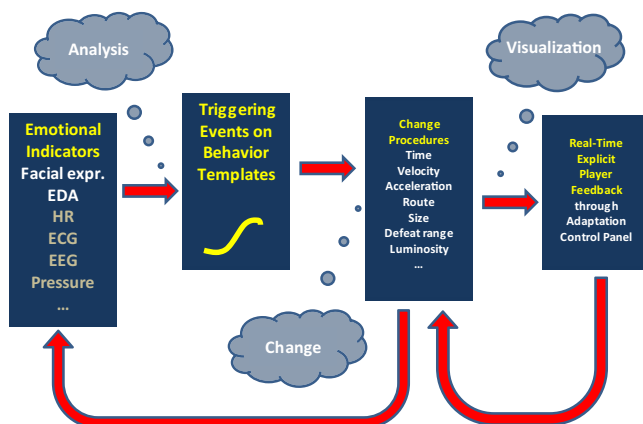
3.3 Affective adaptation control

“Rush for Gold” uses a workflow of emotional adaptation control based on the traditional affective feedback loop (Fairclough and Gilleade, 2012), but introduces to it an additional stage as represented in Figure 2. First, expressed player’s affect is communicated to the adaptation control system by emotion indicators such as facial expressions and/or psychophysiological signals. Second, emotion indicators are analysed and appropriate affect events based on behaviour templates or rules are triggered. Third, triggered events are handled by procedures adapting specific game features to the inferred player’s affect. The adapted features provoke additional player’s affect, which in its turn is transmitted through the loop.

Besides these three traditional stages of affective feedback loop, the game applies a fourth one, where players are asked for explicit player feedback through an Adaptation Control Panel (ACP) shown in Figure 3. ACP is similar to the AffectButton method for reliable and valid affective self-report (Broekens and Brinkman, 2013) in terms of real-time evaluation of affect-based adaptation. However, besides acting as an embedded self-report tool for evaluation of affective adaptation (the slider shown over in Figure 3), ACP provides a functionality for setting both direction and strength of affective adaptation, as well. The slider shown down in Figure 3 allows the player to set at any moment of the game his/her

Table II.
Dynamic correction of
task difficulty by
affectation level
applying positive
affective feedback

Emotion valence	Positive emotion (E)	Arousal (A)	Affectation level	Task difficulty	Light intensity
Negative	$E \geq 0.4$	$A \geq 7$	High	Rather lower	Rather darker
Negative	$0.2 < E < 0.4$	$3 < A < 7$	Moderate	Slightly lower	Slightly darker
Negative	$E \leq 0.2$	$A \leq 3$	Low	Not changed	Not changed
Positive	$E \geq 0.4$	$A \geq 7$	High	Rather higher	Rather brighter
Positive	$0.2 < E < 0.4$	$3 < A < 7$	Moderate	Slightly higher	Slightly brighter
Positive	$E \leq 0.2$	$A \leq 3$	Low	Not changed	Not changed



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Figure 2.
Workflow of the
affective adaptation
control

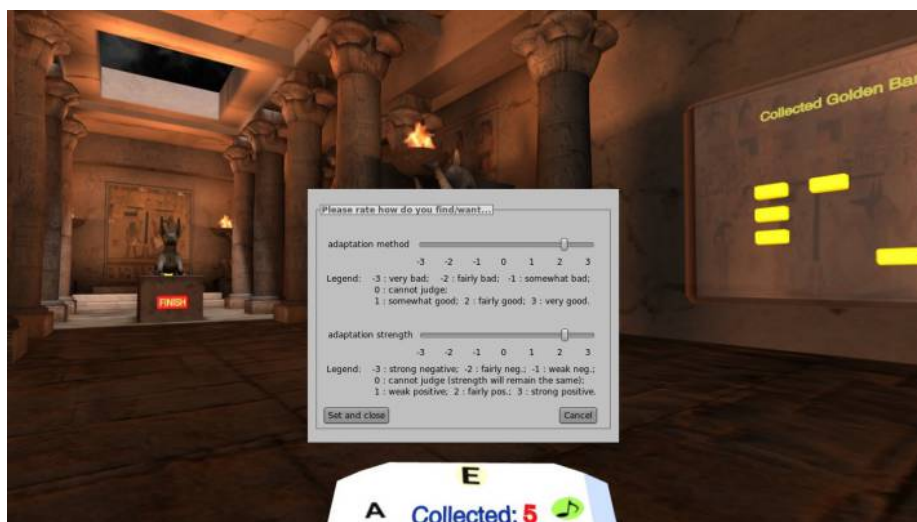


Figure 3.
A view of the built-in
ACP

preferred direction of affective adaptation of task difficulty and light intensity by selection an integer value from +1 to +3 for positive affective feedback and from −1 to −3 for the negative one. At the same time, strength of affective adaptation is set to weak (for values +1 or −1), medium (for +2 or −2) and strong (for +3 and −3). The value set by default is +2, that is, fairly positive adaptation. The selected value is sent immediately as explicit player's feedback to the affective loop and applied to change its strength and, in cases of passing from positive to negative or vice versa, its direction. Change of loop direction from positive to negative inverts the control outlined in Table II, whereupon positive emotions start invoking decreases of task difficulty and light intensity. On the other hand, changing the slider value from +2 to +3 results in a stronger positive adaptation, where both task difficulty and light intensity will be adjusted in the same way but using a higher scale. Thus, players are able not only to correct the strength of applied affective adaptation but to change its direction, as well.

4. Practical experiment

4.1 Experimental setup

For conducting the experiment, a software/hardware setup was assembled on a single gamer laptop. The software setup included the “Rush for Gold” applied video game with both performance-based and affective adaptation of game tasks and visual effects. “Rush for Gold” was applied for implicit recognition of both playing and learning styles, which were communicated to an educational maze game with leaning content about strategic business management adapted to the recognised individual style. Both “Rush for Gold” and the maze video game were developed by means of the Brainstorm eStudio platform[1] using music, textures and 3D visual objects specially designed for this purpose.

Figure 4 presents the software architecture of the experimental setup. By means of TCP sockets, both the games were integrated with two external software applications – one for measuring player’s arousal (RAGE[2] arousal recognition asset shown on the right side of the figure) and another for emotion recognition based on facial expressions using Affectiva SDK[3] (referred as Emotion recogniser on the left side).

The RAGE software asset (Real-Time Arousal Detection Using Galvanic Skin Response Asset) is a software component receiving raw EDA signal from a custom measuring device (Figure 5) and processing it in real time to infer player arousal. It applies high and low pass software filters to extract background tonic SCL reflecting general changes in autonomic arousal (lasting tens of seconds or minutes) and phasic changes known as SCR produced by sympathetic neuronal activity. The time window applied was 10 s, and the calibration period (finishing with starting the game session) was 2 min. The asset applied 160 Hz sampling rate with eight times downsampling and returns:

- phasic arousal level (set from one to ten);
- tonic arousal level (set from one to ten);
- moving average of the raw EDA signal;
- phasic activity represented by amplitude of skin conductance response, SCR rise time, SCR $\frac{1}{2}$ recovery time, response peaks/second and average area under the curve per second; and
- tonic activity represented by the slope of tonic activity (tangent of the slope angle of the tonic signal) and amplitude of the skin conductance level.

Together with the emotions inferred on facial expressions, phasic arousal level was applied for tailoring difficulty of the shooting and discovering tasks. The Emotion recogniser (Figure 6) estimates player’s emotion levels (in percentage) by means of face expressions analysed by

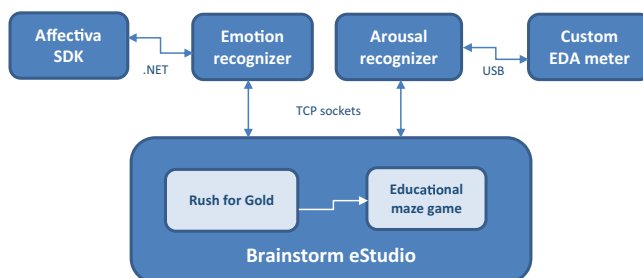
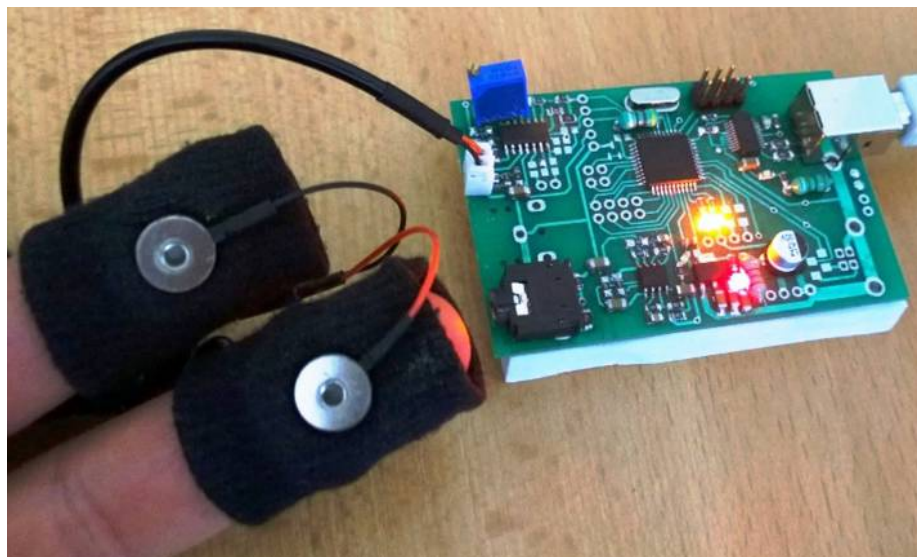


Figure 4.
Software architecture
of the experimental
setup



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Figure 5.
Usage of the custom
EDA measuring
device

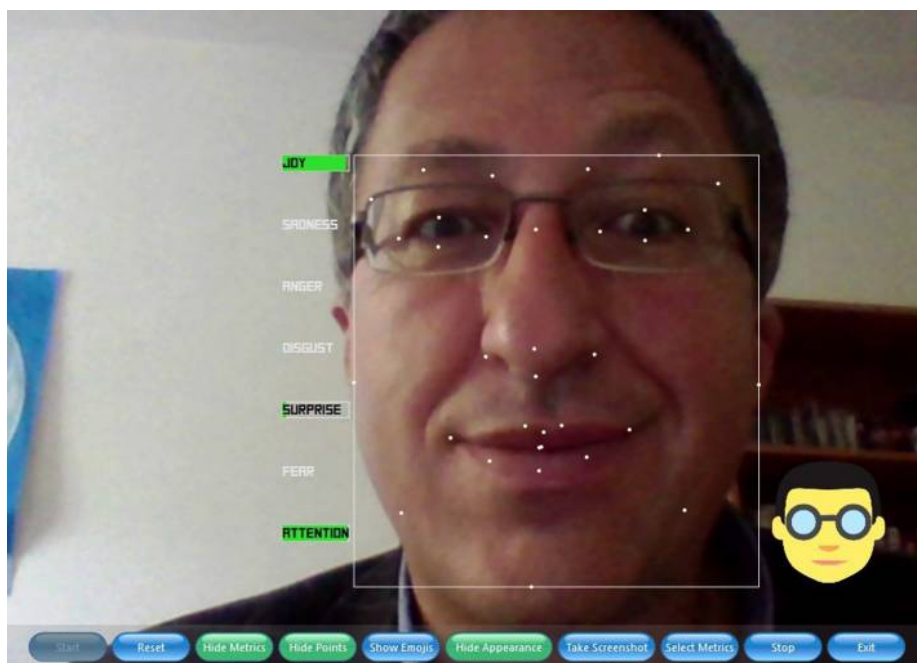


Figure 6.
A screenshot of the
emotion recognition
application

applying a rate of 15 Hz. The estimation software is a client side application using video stream produced by the Web camera of the computer/laptop. Data about the six basic emotions are averaged within a moving window of 10 s. Affective adaptation was applied for DDA of both shooting and discovering tasks (as shown in Table II) and, as well, for controlling light intensity.

After gaming sessions, a combined 92 items questionnaire was conducted by anonymous self-completion via internet. The questionnaire consisted of four sections, as follows:

- (1) questions about player demography including sex, age, marital and employment status and education;
- (2) questions about previous gaming experience and amount of video gameplay of the subject (Ventura *et al.*, 2012);
- (3) ADOPTA PS questionnaire (Bontchev, 2016); and
- (4) questions about affect-based game adaptation.

4.2 Procedure

The experimental procedure included subject selection, gaming sessions' appointment and performance and post-game self report by filling online the questionnaire outlined over. Before gaming sessions, a consent form (translated in Bulgarian) was signed by each individual participant. Participants played the game on a gamer laptop with 15" LCD using a Logitech wireless mouse and the custom EDA measuring device. AgCl electrodes were placed at the palmar and hypothenar eminences of the middle and ring fingers of the player's non-dominant hand (Boucsein, 2011). To avoid pressure artefacts, participants were instructed not to use these fingers while playing.

After individual explanation about the experiment, short demonstration and a procedure of informed consent, each participant was asked to spend 2 min in relaxation, with the electrodes placed on his/her fingers, while listening to calm music and watching playing instructions. Next, after pressing the start button, a signal about end of calibration period was communicated to the EDA meter. The player was asked to perform a short assisted training session playing "Rush for Gold", followed by two game sessions in random order – one without and another with affective adaptation control. During the session with adaptive gameplay, players were asked to use the ACP built into the game to evaluate affective adaptation and to set its strength preferred by them. After playing "Rush for Gold", the player was automatically transferred to an educational maze game with learning content adapted to the recognised individual style of the participant. No background music was played during the sessions other than game music and event-related sounds such as at shooting and hitting.

After the gaming session, each player was asked to fill in the combined online questionnaire. After finishing that activity, the participant was asked to share his/her personal impressions of all the phases of the experiment. Finally, he/she was thanked and was awarded with a flash memory stick as a gift.

4.3 Participants

The experiment was conducted within two weeks in June 2016, with participation of master students and lecturers at the Faculty of Mathematics and Informatics at Sofia University, Bulgaria. By means of email announcement, there were selected 30 volunteers (average aged near 31, with gender balance of 18 men and 12 women), who all passed individually the procedure described over. Experimental sessions were scheduled in Doodle and took in average about 90 min each.

The post-game survey revealed significant previous gaming experience of the participants. As represented in Table III, 90 per cent of them were experienced in gaming, but taking mostly several hours per week, with coding as follows: 0-2 h weekly, 2-6 h weekly and 6 or more hours per week (Ventura *et al.*, 2012). Only three of the subjects reported to spend playing 6 or more hours per week. The coding of average hours played per game is as follows: up to 10 h, from 10 to 50 h and 50 h or more. The majority of the participants appeared to be moderate players. The last question was “How many different video games do you typically play in a year?” with possible answers: 0-3 games, 4-6 games, 7 or more games per year. Moreover, 18 of the participants (60.0 per cent) reported 0-3 games, and only two (6.67 per cent) selected the third answer.

5. Analysis of results

This section presents some of the experimental results concerning the effect of affective adaptation over game session time, task’s effectiveness, efficiency and difficulty and, on the other hand, players’ assessment of affectively adaptive gameplay.

Figure 7 depicts box plots of efficiency (ratio between results and effort) of shooting, discovering and solving tasks, in non-adaptive and adaptive affective modes. As a common and beneficial trend for adaptive affective mode, efficiency of tasks of all the types is increased. In addition, the position of the median and the reduction of outliers reveal that in adaptive affective mode results possess better normality of distribution than without such adaptation. The same is valid for the box plots of task difficulties in non-adaptive and adaptive affective mode (Figure 8).

Besides efficiency and difficulty, average task’s effectiveness (i.e. result measured in collected bullions) was improved in affectively adaptive mode, as well. Table IV shows average relative improvements in task’s effectiveness, efficiency and difficulty due to affectively adaptive gameplay measured as average of differences between values obtained in both the modes and divided by the value in non-adaptive affective mode. We performed paired two-tailed *T*-tests to compare these chief game metrics of shooting, discovering and puzzle-solving tasks, based on using or not using the affectively adaptive gameplay. For all

Statistic	Age	Gender balance	Gaming experience	Hours weekly	Hours/game	Games/year
<i>M</i>	31.867	0.600	0.900	1.333	1.852	1.407
<i>SD</i>	10.051	0.498	0.305	0.620	0.864	0.636

Notes: *M* = Mean; *SD* = Standard deviation

Table III. Demographic data and gaming experience

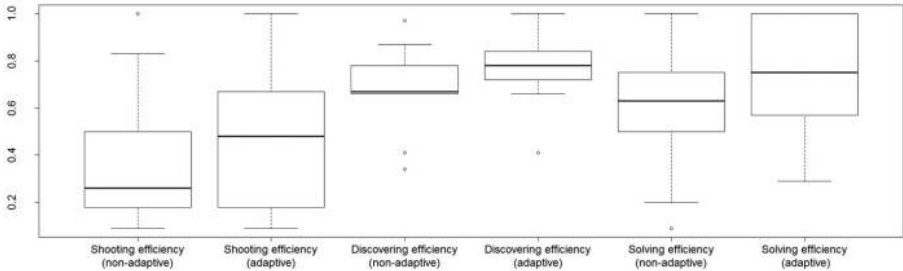


Figure 7. Box plots of task efficiencies in non-adaptive and adaptive affective modes

Figure 8.
Box plots of task
difficulties in
non-adaptive and
adaptive affective
modes

the values of efficiency and difficulty, we obtained p -values less than 0.05 (given in *italics*) and, for some of them, less than 0.001. Therefore, these results reject the null hypotheses with high confidence and indicate that the improvements in task's efficiency and difficulty due to emotionally adaptive gameplay are statistically significant.

Similarly, [Table V](#) presents average relative improvement in overall result, game session time, relative time (for collecting a bar of gold) and AE and difficulty when applying adaptive gameplay. It provides p -values obtained by paired two-tailed T -tests to compare these metrics based on using or not using affectively adaptive gameplay. These p -values appeared to be less than 0.01 for the session time and less than 0.001 for AE and difficulty (all given in *italics*), which indicates that the differences in game session time and AE and difficulty due to affectively adaptive gameplay are statistically significant.

After finding statistically significant differences in player's metrics due to affectively adaptive gameplay, we could expect a relative improvement in implicit recognition of playing style due to the same reason, as far as styles are calculated by means of linear regressions using the same player's metrics. [Table VI](#) shows average relative improvement in mean accuracy of style recognition thanks to affectively adaptive gameplay. Each style is calculated twice – once by using linear regression coefficients determined by structured interviews with game-based learning practitioners and once by coefficients found by the

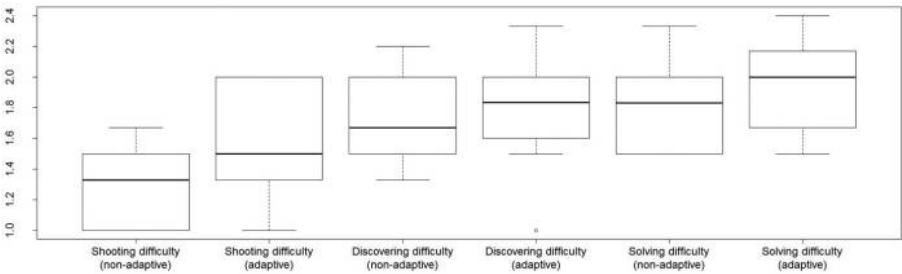


Table IV.
Average relative
improvement in task's
effectiveness,
efficiency and
difficulty due to
affectively adaptive
gameplay

Task	Effectiveness	Metrics Efficiency	Difficulty
Shooting task (%)	14.50	61.15	24.98
<i>p</i>	0.394364	<i>0.043489</i>	<i>0.000005</i>
Discovering task (%)	16.33	16.24	8.58
<i>p</i>	0.669210	<i>0.002680</i>	<i>0.022826</i>
Solving task (%)	14.33	46.43	6.81
<i>p</i>	0.561831	<i>0.000243</i>	<i>0.005414</i>

Table V.
Improvement in total
result, game session
time and average
efficiency and
difficulty due to
affectively adaptive
gameplay

Statistic	Overall result	Player metrics			
		Session time	Relative time	Average efficiency	Average difficulty
Increase (%)	5.45	-11.29	32.88	24.38	12.61
<i>p</i>	0.084997	<i>0.006133</i>	<i>0.002212</i>	<i>0.000093</i>	<i>0.000165</i>

least mean squares method. Results reveal statistically significant relative improvements (p less than 0.01) in the mean accuracy of style recognition of competitor, logician and strategist.

During the experiments, assessment of affective adaptation was obtained in two ways:

- (1) using the ACP embedded into the game and reachable by the button E (Figure 1); and
- (2) applying post-game questionnaire including questions about player's preference of affectively adaptive gameplay and degree of liking adaptive control of light intensity and DDA of shooting and discovering tasks.

Both the ACP and self-report assessment show high appreciation of affect-based adaptation methods. For comparing ACP to self-report assessment, ACP scores were converted from seven-point Likert scale (Figure 3) to the more popular five-point scale used for the questionnaire. For players having assessed affective adaptation through ACP more than once, ACP assessments were averaged for the game session. Table VII shows comparison of overall affective gameplay by means of in-game ACP and post-game questionnaire. Mean values (M) of assessment of overall affective adaptation are rather high and very close to each other; however, standard deviations (SD) are significantly higher for all post-game self-reports than SD of ACP results. Next, the table presents product-moment correlations (Pearson r) between ACP assessment and questionnaire results, together with p -values of Student's paired t -test, with a two-tailed distribution. The result reveals strong and highly statistically significant correlations (p less than 0.0001) between assessments done by the in-game graphic tool for adaptation's evaluation and control and, on another side, by the post-game questionnaire. The Cohen effect size (Cohen d) is small for the mean difference between the two groups assessing overall affective gameplay, which reveals their interchangeable use. Cohen d is medium for the rest of mean differences, which can be explained by the specific assessment of affective adaptation through post-game self-report. On the other hand, the relative per cent error (evaluated as the difference between each ACP assessment and corresponded self-report, divided by the ACP value) appears to be approximately between 11 and 15 per cent.

Table VI.
Average relative
improvement in mean
accuracy of implicit
recognition of playing
styles due to
affectively adaptive
gameplay

Statistic	Playing style							
	Competitor (SI)	Competitor (LMS)	Dreamer (SI)	Dreamer (LMS)	Logician (SI)	Logician (LMS)	Strategist (SI)	Strategist (LMS)
Improvement (%)	28.99	49.18	17.83	22.95	25.26	24.79	16.27	19.12
p	0.003566	0.0273333	0.120523	0.071007	0.039713	0.034220	0.000005	0.000001

Table VII.
ACP in-game
assessment of
affective adaptation
compared to post-
game self-report

Statistic	Assessment of affective adaptation				
	In-game ACP Overall affective gameplay	Overall affective gameplay	Post-game self-report DDA of shooting task	DDA of discovering task	Adaptive light intensity
M	4.50490	4.366667	4.066667	4.133333	4.233333
SD	0.477670	0.850287	1.048261	0.973204	0.858360
r		0.65753	0.81853	0.83962	0.86386
p		0.00008	0.00000	0.00000	0.00000
d		0.200448	0.537999	0.484706	0.390966
Relative error (%)		11.3108	13.7569	15.2001	11.0900

6. Discussion

Experimental results presented in previous section clearly prove the expected benefits of affect-based DDA concerning playing outcomes (*RQ1*). Affectively adaptive gameplay brings better distribution normality and increases task's efficiency and difficulty with a statistically significant effect and, on the other hand, reduces game session time and relative time for performing a single task. As expected, better playing outcome thanks to the affectively adapted gameplay leads to an improved recognition of PS (*RQ2*). Although average accuracy of playing style recognition by means of using linear regression when applying performance-based adaptation only is 64.3869 per cent, average accuracy of playing style recognition when applying both performance-based and affective adaptation amounts to 82.4311 per cent (p less than 0.001). Thanks to the fact that ADOPTA playing style appeared to be highly correlated to learning style of Honey and Mumford, PS recognised by the game can be use as indicators of learning styles, as well. Both predicted PS and LS can be applied further for style-based adaptation of learning content in educational video games and for achieving a better studying motivation and learning outcomes.

Players' assessment of affectively adaptive gameplay by means of both in-game visual tool for adaptation's evaluation and post-game self-report was found strictly positive (*RQ3*). All the players enjoyed affective adaptation mode and played the second game session (the adaptive one) most of the time, with mean relative time in affective adaptation mode equal to 94.80 per cent. Only two of the participants experimented negative affective loop with average strength of adaptation -2.5 and -3 and reported it as enjoyable. All other players ($N = 28$) appreciated adaptive gameplay with positive affective loop selecting average strength of adaptation near moderate ($M = 2.307857$, $SD = 0.675137$). Moreover, both the visual tool and self-report method demonstrate strong and statistically significant correlations of assessment results. The results validated the ACP as a useful and accurate assessment tool. Thanks to the fact that it is embedded into the game and allows evaluation of adaptation in real time, it appears a better and a more ecological instrument than a post-game survey. On the other hand, players do not think about assessment while playing; therefore, they have to be asked explicitly for doing it.

7. Limitations of the study

The experiment described in this article is conducted under several limitations. First of all, the designed instrument (the "Rush for Gold" adaptive video game) does not serve for general recognition of any playing style but only for ADOPTA PS outlined in Section 2.4. Other experiments have proved that the game recognises LS of Honey and Mumford (1992) with an accuracy similar to ADOPTA PS recognition. Therefore, recognised styles are limited to such based on the Kolb's Learning Style Inventory (Kolb, 1984).

Another limitation of the study was the relatively small number of participants ($N = 30$). Limitation was imposed by the extended procedure of the experiment including a short demonstration, an assisted training session and two game sessions in random order – one without and another with affective adaptation control. Future experiments should take more time to include more participants for checking if increases of task effectiveness would become statistically significant and to prove the other results for a higher N . Another obstacle for experimenting with a greater number of participants was the limitation of the instrument developed as a desktop game. An adaptive Web-based game (at least applying affect-based recognition using facial expressions but not EDA sensors for arousal detection) will facilitate experiments with hundred and even thousands of game sessions not limited to place and time. Moreover, it will allow testing reliability of the playing style recognition method by performing multiple game sessions in a given mode for a single player.

8. Conclusions

Applied games using LS and/or PS for adaptive gameplay and personalisation of learning materials are still an unexplored but rather promising research area. Lindberg and Laine (2016) envisage three main reasons for style-based adaptation for games for learning: best perceiving and processing of learning materials, easier acceptance of game mechanic and increased player's motivation and engagement. The present article described a novel and ecological approach for implicit recognition of PS during playing a game, which offers good accuracy thanks to an emotionally adaptive gameplay in combination with adaptation based on player's performance. Player's affect was recognised by applying both arousal level detected through EDA measurements together with emotional state inferred according to facial expressions. For a flexible control and assessment of the affective loop, the game used a graphic interface for setting both strength and direction of affective adaptation and for assessing it during the game. This assessment, together with the post-game self-report, proved the game is pleasant and intriguing for the players.

Affect-based adaptation of gameplay was introduced with the intention to bring benefits concerning playing time and better efficiency and difficulty of completed tasks compared to the non-adaptive gameplay. Experimental results presented in the article prove this research hypothesis about expected benefits of affect-based DDA concerning playing outcomes. Positive assessment of affective adaptation was confirmed by means of both the in-game tool (ACP) and the post-game self-report, with a strong correlation of the assessment grades. Besides benefits concerning playing outcomes and preference to play, affectively adapted gameplay meliorated the mean accuracy of implicit recognition of PS with relative improvement starting from 16.27 up to 49.18 per cent.

Initial experiments with "Rush for Gold" proved the expected beneficial impact of affectively adaptive gameplay over the accuracy of implicit recognition of ADOPTA PS during the game session. At the same time, it was found that besides implicit recognition of PS, the game also recognises LS of Honey and Mumford (Bontchev, 2016), with a similar recognition accuracy. Recognition of both ADOPTA PS and LS of Honey and Mumford was validated by means of post-game questionnaires and is due to the fact both they are based on the Kolb's Learning Style Inventory model. Thus, after finishing the "Rush for Gold" game, the player is transferred to another educational maze game, applying found playing (and hence learning) style for a style-based adaptation of learning content. Therefore, "Rush for Gold" results about the styles of an individual learner can be successfully applied for adaptation of educational games based on playing or learning styles.

Notes

1. Available at: www.brainstorm.es/products/estudio/
2. Available at: <http://rageproject.eu/rage-ecosystem/>
3. Available at: www.affectiva.com/

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