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Intelligent Adaptation of Difficulty and NPC Behavior in Serious Video Games for Learning

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Abstract: User-centric adaptation of serious video games continues to be a very important issue because of its benefits, such as enhanced motivation and engagement of individual players. It is based on player/learner characteristics that can be measured, estimated, recognized, or found by classification or clusterization. The paper suggests a new approach for dynamic, user-centric tailoring of task difficulty and the behavior of non-player characters. The approach is based on the emotional state and the shown outcomes of the individual player. Recognizing the current emotional state is based on facial expression analysis by convolutional neural networks and on an analysis of physiological data measured by sensors while playing the game. There are provided examples of serious games of learning with a dynamic adaptation of task difficulty and non-player character behavior.

Keywords: Serious video games, adaptation, dynamic, non-player character, educational.

1. INTRODUCTION

Since their invention in the seventies of the last century, video games have continued enjoying great success and recognition among different generations, thanks to their high interactivity, attractive gameplay, and intriguing stories (Lebowitz & Klug, 2011). Unlike video games for fun, serious (or also called applied) video games have a primary goal different from pure entertainment (Abt, 1987). Serious video games for learning (or educational video games) represent their most popular subdivision that applies to didactics (Connolly et al., 2012). During the last decades, the massive usage of game-based learning appeared to be a great promoter for the design and application of such games in schools and universities. For effective and efficient game-based learning, the game player (i.e., the playing learner) should be highly motivated, engaged, and kept in flow – a state of balance between the individual skills and the challenges provided by the game (Sweetser et al., 2017), while playing a serious game for learning. The importance of user-centric adaptation in educational video games emerges exactly from this goal: tailoring various game issues according to player/learner characteristics and, thus, keeping him/her in the flow and increasing both the intrinsic motivation and engagement to play educational games. For example, dynamic difficulty adjustment (DDA) in educational games is proven to increase both game playability and learnability (Bontchev, 2022). The approaches for a user-centric adaptation of video game features based on player/learner characteristics rely on player modeling and tracking, recognizing, or estimating specific players' features for applying them to tailoring the game. Hence, as a base of user-centric adaptation (Terzieva-Bogoycheva, 2023), there are used two types of personal characteristics: the player's emotional state and playing outcomes (i.e. results) as indicators of individual player skills. The methods of implementing user-centric adaptation using player emotions (Hudlicka, 2008) recognize current emotional state through (1) Facial expression analysis – provided the game has access to the player's camera and, thus, can process its video stream or separate images of the player's face; (2) Gesture expression analysis – important for dance games or rehabilitation games; (3) Analysis of physiological data; (4) Analysis of speech. The authors have identified two key issues of user-centric adaptation of video games for learning:

1. Tailoring the learning task difficulty – it is very important because didactic tasks are mapped to gaming tasks;

2. Adapting the behavior of non-player characters (NPCs), i.e., virtual heroes (Yunanto et al., 2021) – applied in educational games for (a) teaching assistants (the most popular case); (b) concurrent learners; or (c) opposite characters or enemies.

The paper discusses a novel approach for dynamic adaptation of learning task difficulty and NPC behavior based on a combination of recognition of the individual emotional state and tracking game outcomes. As methods to recognize the individual emotional state, we apply convolutional neural networks (CNN) over facial expression data (Yunanto et al., 2021) and, on the other hand, clusterization of physiological data (Goodfellow et al., 2016). We compare the benefits and shortcomings of these two methods and, next, discuss how the recognized emotional state of the individual game player can be used for dynamic tailoring of task difficulty and NPC behavior, in combination with player outcomes tracked during gameplay. In the next section, we discuss some examples of tailoring task difficulty and NPC behavior in serious games for learning. The paper finishes with a conclusion about the applicability of the proposed approach to combining both player's emotional states and outcomes.

2. BACKGROUND WORKS

The section provides an overview of existing approaches and methods for user-centric adaptation of educational video games, with a focus on these based on recognition of the

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player's emotional state and outcomes demonstrated during gameplay.

2.1 User-centric adaptation of serious video games

The goal of the user-centric adaptation of a video game is to enhance the overall playability and/or learnability of the game (Hudlicka, 2008). An adaptation that is based on the emotional state of the player makes the gameplay affective (Bontchev, 2016). Affective video games with tailoring based on the emotional state apply three types of mechanisms for dynamic tailoring the gameplay, namely: (1) adjustment of explicit, implicit, or player-driven game tasks; (2) adaptation of difficulty towards individual anxiety or skill level; (3) tailoring of audio-visual properties such as ambient sound.

Bersak et al. (2001) coined the term *affective feedback loop*, where the program learns how the game or the environment affects the psycho-physiological user's state and, next, adjusts its behavior according to user changes. The affective feedback loop may use positive or negative feedback depending on the current need to adjust specific game features. The program is supposed to infer the emotional state of the user, either by recognizing it, by classification, or by an estimation of the physiological responses received from the users (Bontchev, 2016). The APOGEE project applied a holistic model of user-centric adaptation of a video game joining emotion-based game adjustment with tailoring game features based on playing styles and player outcomes (Bontchev, 2022). The model is proven to enhance both motivation and engagement of the individual player while keeping the player in flow, i.e. in an optimal balance between playing skills and in-game challenges.

2.2 Recognition of the emotional state of the player

Emotions are complex psycho-physiological states triggered by a specific stimulus. Understanding the complexity of emotions is key to unlocking their full potential and harnessing their power to improve our lives. They are typically categorized into basic emotions such as happiness, sadness, anger, fear, surprise, and disgust (Ekman et al., 1969), but can also include more complex emotions like frustration, excitement, and boredom. Recognizing emotions from facial expressions is important for understanding human behavior, communication and social interaction, user experience and human-computer interaction, and psychological and mental health assessment.

2.2.1 Analysis of facial expressions

Recognizing emotions from facial expressions is important as it contributes to our understanding of human behavior, enhances communication and social interactions, improves user experience in technology applications, and assists in psychological and mental health assessment. It ultimately helps us create a more empathetic and emotionally intelligent society. Ekman, Sorenson, and Friesen (1969) developed methods for facial expression recognition of six basic universal emotions as a basis for non-verbal behavior. For the analysis of facial expressions in recognizing the emotional state of players, different methods can be used such as feature extraction using facial landmarks, template matching, classification using machine learning models like KNN, SVM, etc., and deep learning models (Goodfellow et al., 2016).

2.2.2 Measurement and analysis of physiological data

There are three main groups of emotion measurement strategies (Bontchev, 2016): self-reports, observational methods, and psychophysiological measurements. Self-report provides details about emotions, with the subject completing special questionnaires to describe their current or past emotions. Bradley and Lang (1994) developed the Self-Assessment Manikin (SAM) as an effective visual alternative to traditional verbal self-reports. Observational methods are based on observing, recording, and interpreting a person's body or behavior to infer specific emotions. The analysis of physiological data is a method with the help of which the recognition of emotions occurs naturally since physiological activities and changes are directly related to the processes in the central and autonomic nervous system. Physiological data are translated into physiological states by extracting specific characteristics from already measured physiological signals (Picard et al., 2001) such as Electrocardiograph (ECG), Blood Volume Pulse (BVP), Galvanic Skin Response (GSR), and Electromyography (EMG).

2.3 Playing and learning outcomes

Playing or/and learning outcomes are traditionally used for dynamic difficulty adjustment (DDA) in video games (Hudlicka, 2008). Playing outcomes are results achieved during a gaming session when the player solves a typical game task, such as hitting a moving object or finding a hidden item while learning outcomes are results obtained from solving a didactical task like solving a puzzle. Examples of such outcomes are playing/learning effectiveness (the total effect/result obtained from playing a serious game for learning), efficiency (the effect divided into the effort or time for obtaining it), and playing time. These outcomes represent gameplay metrics and can be used together with other player characteristics. For example, the "Rush for Gold" serious game applies metrics such as relative time, average efficiency, average normalized difficulty, and average normalized effort, together with player attention and engagement (recognized by facial analysis) and EDA (measured and analyzed by signal decomposition), for tailoring the game difficulty (Bontchev, 2016). The practical validation proved the expected beneficial effect of adaptation of difficulty of didactic tasks over the overall playability and learnability of serious games applied to learning.

3. DYNAMIC GAME ADAPTATION BASED ON THE PLAYER'S EMOTIONAL STATE AND OUTCOMES

The study follows a novel approach that combines recognition of the emotional states of the individual player with tracking of playing outcomes, for applying them as a basis for dynamic game adaptation. The approach is going to be used for two purposes:

1. For dynamic difficulty adjustment of game tasks;
2. For dynamic adaptation of NPC behavior, in order to achieve a credible and believable virtual character.

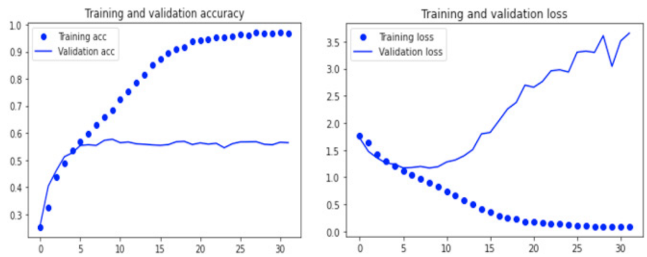

Figure 1. Training and validation accuracy (left) and loss (right) of the neural network.

3.1 Recognition of player's emotional state by CNN

In this research, the chosen method of facial expression analysis is to use Convolutional Neural Networks (CNNs). CNNs are a type of deep neural network architecture that is popular for image recognition tasks because of their ability to extract automatically meaningful features from raw image data (Goodfellow et al., 2016). They are able to learn to recognize patterns at different levels of complexity, which is crucial for recognizing emotions from facial expressions in images. Facial expression analysis using CNNs involves training a model on labeled images of different emotions. The model could learn the features that are present in each image which can be used to recognize different emotions. Once trained, the model can then be used to predict the emotional state of a player from an input image. The used dataset was obtained from Kaggle (https://www.kaggle.com), a platform for data science competitions and a community of data scientists and machine learning practitioners. The dataset consists of 35,885 entities in CSV format, with three columns: emotion, pixels, and usage. The emotion column specifies one of seven emotions, including anger, disgust, fear, happiness, sadness, surprise, and neutral. The pixels column represents the image data in 48x48 pixel size. The usage column indicates whether an entry is used for training, validation, or testing, with 28,709 entries for training, 3,588 for validation, and other 3,588 for testing.

The neural network architecture consists of 779,718 neurons organized into 17 layers divided into four blocks. Each of the first three blocks contains three convolutional layers and one pooling layer. Convolution layers apply filters or kernels to extract local features, like edges and textures, from the input image. Pooling layers are applied after convolution to reduce the spatial dimensions of the feature maps using techniques like max pooling or average pooling. The final block includes a fully connected layer, which combines the high-level features extracted from previous layers to produce the final classification output.

The training accuracy and loss, as well as the validation accuracy and loss, were plotted to evaluate the model's performance during training and testing. The training loss measures the error between the predicted and actual outputs on the training data, while the validation loss measures the error on a separate validation dataset not used during the training. The goal is to minimize both losses, with a significantly higher validation loss indicating potential overfitting. Categorical cross-entropy was chosen as the loss function for multi-class classification, measuring the difference between predicted

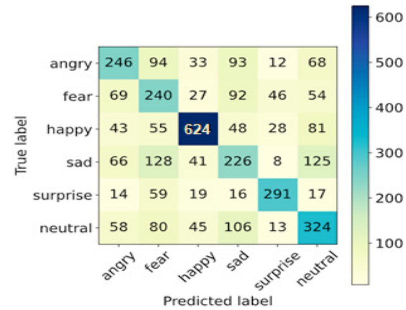

Figure 2. Confusion matrix of neural network.

probabilities and actual labels. Figure 1 shows that the model starts to overfit around the 10th epoch, indicating that it becomes specifically trained for the training data. The model achieved a training accuracy of 68.58% and a validation accuracy of 57.65%. The corresponding training loss was 0.8336, and the validation loss was 1.1942. After training, the model was evaluated using test data images, resulting in an accuracy of 56.84%. The confusion matrix, shown in Fig. 2, reveals that the 'happy' label was most successfully classified. Additionally, the most misclassified label pairs were 'neutral-sad' and 'sad-fear'.

3.2. Recognition of player emotional state by clusterization

With the help of sensors, we can extract physiological data that we will use at a later stage to analyze and recognize emotions through data clustering. Cluster analysis groups similar objects together while keeping them distinct from dissimilar objects in other groups, i.e., other clusters. For the purpose of the paper, we used machine learning clustering algorithms such as K-Means, Mean-shift, and agglomerative clustering provided by the scikit-learn library (INRIA, 2023), based on the Python language, applying them to physiological data such as BVP and EDA extracted using a device Human Monitor GS-02 (Ivanov et al., 2019). Mean-shift is a non-parametric mean-shift clustering algorithm that is density-based and can be used to identify clusters in a dataset (Comaniciu & Meer, 2002). This is extremely useful when the clusters formed by a data set have arbitrary shapes and are not well separated by linear boundaries.

The data that will be used for emotion analysis were extracted from volunteers who participated in the experiment from different age groups and genders (5 men and 5 women between the ages of 20 and 50 with different education and profession). For the experiment, the device Human Monitor GS-02 (Ivanov et al., 2019) was used, with the help of which data on heart blood volume pulse (BVP) and skin resistance, or galvanic skin response (GSR), were collected from each participant. The experiment lasted 20 minutes, during which each of the participants was asked to watch short films provoking four of the main emotions (Joy, Sadness, Fear, Anger). Watching videos was preferred instead of playing video games because this is the easiest and fastest method to invoke specific human emotions in a controlled way. The order of the video films in the experiment was randomized so that the sequence of the video films was different for each participant as much as possible. To isolate the emotional response evoked by the different videos, after the end of each video, there was a pause of 1 to 2 minutes, intending to allow the participant to rest, and

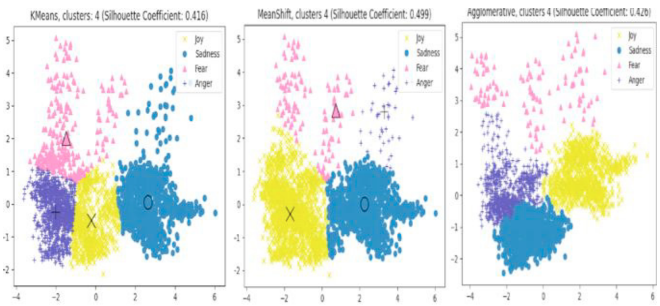

Figure 3. K-Means (left), mean-shift (middle), and agglomerative (right) clustering based on physiological data.

within this time, the data was annotated. The subject was connected to the Human Monitor GS-02 device (Ivanov et al., 2019), which in turn detects the participant's physiological data while watching a video.

For the purposes of our experiment, we used the clustering of data of blood volume pulse and skin resistance for emotion recognition based on physiological data, and the algorithms we apply are K-Means, MeanShift, and Agglomerative provided by the sci-kit-learn library (INRIA, 2023). Before applying the clustering algorithms to the collected data from the experiment, several steps need to be performed. Each participant's data is saved in two text files, one stores information from the BVP sensor, while the second stores information from the GSR sensor. Based on the information that each subject fills in after the end of each video, we can annotate the data using the following notation for this purpose: 1 - Joy, 2 - Sadness, 3 - Fear, 4 - Anger. The data for each of these files is annotated in this way, after which the files for the corresponding participant are merged.

Figure 3 represents the clustering results of the annotated physiological data. K-Means succeeds in recognizing four emotions by grouping them into four clusters; these are the expected results. We use the K-Means clustering algorithm because this algorithm handles huge amounts of data very well. For the current study, the data we use is so much because the number of participants is limited to 10, but in real conditions, the participants can be dozens of times more, which would lead to the generation of a constant flow of data. For greater accuracy, we have also used Mean-shift and Hierarchical Agglomerative algorithms, which do not require a prior setting of the number of clusters. It can be seen that the last two algorithms confirm the result of the K-Means clustering algorithm, grouping the data into four clusters.

3.3 A method for dynamic tailoring of video games

Here, we present a general approach for dynamic, user-centric tailoring of various issues within a video game, based on the emotional state and the demonstrated outcomes of the individual player. Addressing the adaptation control using the six (or even four) basic emotions (Joy, Sadness, Fear, Disgust, Anger, Surprise, Neutral) is a very complex problem. In order to simplify it, we group the four basic emotions as (1) fear and sadness – not desired, context-dependent emotions, and (2) joy and anger – desired, context-dependent emotions. The DDA control may increase (abbreviated as Incr) or decrease (Decr) the difficulty of the current task, or may resolve not to change it (Const). All the changes (upwards or downwards) are executed in one step, only if the new value of difficulty D_{new} is

$$Dmin \leq Dnew \leq Dmax$$

In educational games, NPC plays usually a tutor or assistant of the player. Hence, we suggest several basic types of tutor behavior that are not exclusive and can overlap, namely (1) Encouraging, (2) Satisfied/happy, (3) Angry, and (4) Surprised. If there is no NPC in the video game, these types may serve as types of informative feedback issued to the player.

Table 1. Adaptation of difficulty and NPC tutor behavior

No	Desired Emotion	Non-desired Emotion	Out-comes	Diffi-culty	NPC tutor behavior
1	Low	Low	Low	Const	Encouraging
2	Low	Low	High	Incr	Satisfied, encouraging
3	Low	High	Low	Decr	Soothing, encouraging
4	Low	High	High	Decr	Encouraging
5	High	Low	Low	Const	Anger, surprised
6	High	Low	High	Incr	Satisfied
7	High	High	Low	Const	Encouraging, surprised
8	High	High	High	Decr	Satisfied, surprised

Table 1 represents the suggested adaptation control of difficulty and NPC tutor behavior, which is based on desired/undesired emotions and player effectiveness. Here, in situations numbered from 1 to 8, where the player: (1) has played a lot without any engagement and motivation; (2) has achieved a high score and demonstrated good skills but remains apathetic; (3) is disappointed by his/her low outcome; (4) manages to play well but at the price of some non-desired emotions; (5) is happy to play the game but without trying to achieve good outcomes; (6) is happy to play the educational game while achieving a good score; (7) cannot achieve a good score and has both desired and non-desired emotions; and (8) has succeeded in the game but at the price of negative emotions.

Note that DDA has to start after a specific playing time sufficient for (1) achieving some results in the game and (2) changing the initial emotion that the player had when starting the game. Also, DDA is supposed to be: (1) controlled within a given interval of difficulty using minimum and maximum values; (2) based on a simple moving average of the values of emotions and effectiveness; (3) each difficulty level has to be supported no less than a minimum timeout between two consecutive checks.

4. PRACTICAL EXAMPLES OF ADAPTATION OF TASK DIFFICULTY AND NPC BEHAVIOR

The first study involved developing several versions of an educational video game simulating car driving under various weather conditions. The first version of the game does not use any adaptation methods. The second version applies a classic method of dynamic adaptation based on achieved levels of player results. This changes the game's dynamics and difficulty by altering environmental features like fog, rain, darkness, and other factors (Fig. 4). The third version employs a dynamic adaptation method that detects patterns in the player's learning curve.

The methodology of the research involved conducting experiments with players who engaged in different versions of the car driving simulator game. The players' performance data, feedback, and experiences were collected and analyzed. The study aimed to determine the efficiency and effectiveness of dynamically adapting the game's difficulty based on players' cognitive abilities and skills. The results from the study gathered information about players' profiles—demographics, their gaming habits, and preferred game genres; improvement of player performance—results suggest that the adaptive version led to significant improvements in player performance compared to the non-adaptive one; improvement of player experience—players' feedback on the adaptive versions of the game indicated higher satisfaction levels, increased feelings of competence, immersion, flow, challenge, motivation, and positive emotions. Hence, the research findings suggest that dynamically adapting the car driving simulator game based on playing outcomes and learning curve patterns has a statistically significant positive impact on players' performance and experience.

The second study was conducted within the APOGEE project, where NPC behavior was adapted according to the tracked player outcomes while playing an educational game about the medieval history of Bulgaria (Bontchev, 2022). Fig. 5 presents two of the developed NPC's being tutors of the player. Their emotional state is represented in a simplified way—first by an emoticon showing a HAPPY state and, as well, as a transition (the horizontal bar left from the emoticon) being in progress to an ANGRY state. The percentage of filling of the horizontal bar with red color shows the progress of the transition from HAPPY to ANGRY emotional state of the NPC—when the bar is 100% red, the NPC will trigger from HAPPY to ANGRY state. Here, all the transitions are executed according to the tracked performance (outcomes) of the player within the game. The obtained results revealed that players appreciate the highly adapted behavior of tutoring NPC's and find it more convincible and realistic.

Figure 4. A screenshot of the car driving game.

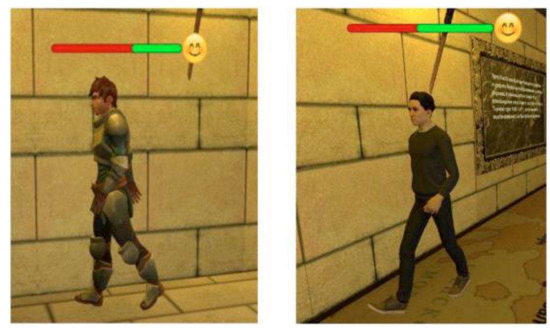

Figure 5. Two NPC's with simplified representation of emotional state (Bontchev, 2023).

5. DISCUSSION

Recognizing human emotions by analyzing video streams or pictures of users' faces is very promising for various online and mobile applications, including video games. Human emotions cannot change very quickly and are manifested after some delay. Therefore, analyzing user face pictures once per second or even less often is sufficient. Also, the time window for changing the difficulty in video games is usually equal to or greater than 10 seconds (Bontchev, 2016). At the same time, this approach may suffer significant drawbacks in specific cases when applied to DDA or tailoring NPC behavior in video games. For example, some players do not manifest their emotions via facial expressions while playing. At the same time, others exaggerate their emotions in order to manipulate the game control and obtain a desired difficulty level by cheating the adaptation controller (Colombetti & Krueger, 2015). For such cases, emotion recognition by physiological signals could be more appropriate, as long as the player cannot cheat the sensors. However, measuring physiological signals by hardware devices and sensors is not appropriate, neither for online games (played at any place and time) nor for playing desktop or console games in mass, even the sensors communicate measured data wirelessly. Hence, new devices and game controllers should be invented, e.g., a mouse or console controller with embedded GSR and BVP sensors.

The outlined studies proved the beneficial effect of emotion-based adaptation of task difficulty and/or NPC behavior over playability parameters. For tailoring the gameplay, one could also apply individual engagement, attention, or motivation, provided he could measure or estimate these metrics. Player engagement and attention, measured together with joy, eye closure, and EDA, can be applied in emotionally-adaptive video games (Bontchev, 2016). Measuring engagement and attention could be problematic, hence, classification or clusterization approaches over physiological data can be applied here. The suggested algorithm shows how task difficulty and NPC behavior can be adapted according to changes in emotions and playing outcomes, however, the approach can be applied to other characteristics of the game, such as game rules, sound, video effects, illumination, etc.

The present study has several limitations. First, the used CNN was trained with a relatively small number of images. To obtain better accuracy and loss, we need to train the CNN with 10 times more images at least. Next, only 10 volunteers participated in the experiments for emotion recognition by clusterization. Finally, the suggested examples of adaptation of video games should be practically validated through practical experiments with real gamers.

6. CONCLUSIONS

In the last two decades, various approaches for user-centric personalization and adaptation of serious video games were suggested, which increased the educational potential of such games following IFAC TECIS and United Nations sustainability goals. In this research, we adapted games applying two types of personal characteristics—the individual emotional state and playing outcomes. To recognize the current emotional state, we applied two orthogonal methods: facial expression analysis through CNN, and, on the other hand, analysis of physiological data measured by sensors during the gameplay.

After presenting some practical results concerning emotion recognition using CNN and clusterization algorithms, we suggested a new approach for dynamic, user-centric tailoring of task difficulty and NPC behavior based on the emotional state and the demonstrated outcomes of the individual player. The approach is general and could be applied for tailoring other features of any serious video game (Aydin et al., 2023) such as game mechanics, informative feedback and help for each game task, educational content, and audio-visual effects.

In conclusion, we would like to state that this approach offers more engaging and tailored gameplay experiences that cater to individual players' abilities and learning progress. This initial study highlights the effectiveness of dynamic adaptation in improving both player performance and experience in a car driving simulator game and a game with NPC with adapted behavior, however, it should be validated through practical experiments with adapted serious games for learning, using the suggested approach. The future field trials are expected to contribute to the growing field of serious games and adaptive gameplay design, showcasing the potential benefits of personalized gaming experiences for education and entertainment.

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