

Analysing Gaming Behaviour: Insights on Personality Traits

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Abstract Educational games have become an integral part of the educational process at various levels, with their usage rapidly increasing as innovative e-learning methods. These games have proven to be highly engaging and effective in knowledge retention. Previous research primarily focused on the impact of violent video games on behaviour and the correlation between game behaviour and personality. Traditionally personality assessment relies on psychometric questionnaires, with the Big Five Inventory (BFI) being a widely used tool. However, these approaches often have certain drawbacks as respondents tend to carefully consider their answers, prioritizing correctness over authenticity. To address these limitations, novel approaches are being developed that incorporate gaming elements to indirectly measure personality. Therefore, an intriguing question arises: Can the subconscious moves, choices, and behaviours exhibited during gameplay serve as indicators of players' personality? In this case study, we developed an educational game focused on Databases courses for university students. The game aims to capture everyday life experiences at the university such as social connections and curiosity or willingness to try new things, based on the Five-Factor Model (OCEAN). The educational content is presented in the form of a quiz with four possible answers, providing appropriate feedback based on the selected responses. The objectives were to strengthen the knowledge and comprehension of Databases subject and also to gather information about players' gaming behaviour and thus predict their scores on two personality traits: Extraversion and Openness to Experience, based on the Five-Factor Model. A total of 149 computer science students of the University of Macedonia participated in the study by playing the game and completing the BFI questionnaire. We utilized classification algorithms to develop a model to predict student's personality. The goodness of the model was assessed using different metrics and the results showed that it is effective to model both the extraversion and openness personality dimensions using serious games instead of questionnaires. These findings can be used by educators and game designers to develop personalized educational games taking into account learner's personality and thus provide valuable insights for future research in this domain.

Keywords: Educational Game, Gaming Behaviour, Gameplay, Personality, Data Analysis

1. Introduction

Educational games are constantly becoming more and more popular. Serious games have significant training potential as they affect the learning process of users in a positive way. The main objective of serious games is to strike a balance between entertainment and interactive education (Noemí and Máximo, 2014). Although assessing the efficiency of an educational game can be quite challenging, recent research findings are notably encouraging regarding the effectiveness of games as educational tools (de Freitas, 2018). Video games have several benefits, for instance, players learn to focus on a desired target and handle situations where multiple events occur simultaneously (Prensky, 2003). Playing games also enhances skills like effectively assimilating information from various sources (Prensky, 2003). In addition, playing educational games increases players' motivation and involvement, leading to enhanced learning outcomes and overall satisfaction (Machado et al., 2018). According to teachers who participated in a survey, student learning is enhanced when educational games are integrated in the school environment (e.g., playing and developing games) (Huizenga et al., 2017). The study highlights essential factors observed by teachers that have an impact on cognitive learning outcomes, including the provision of direct feedback and the facilitation of active learning through discovery. These factors were considered for our game design and development, with personality assessment being the ultimate goal of the study. A common way to measure personality is through questionnaires in a self-report form. The Big Five Inventory (BFI) (John, Naumann and Soto, 2008) is probably one of the most popular questionnaires for personality. However, some questions are arisen regarding their validity as tools for assessing personality. The limitation of these methods is the potential of hiding information on purpose when the respondent will not benefit from answering sincerely (Chen and Lin, 2017). Tlili et al (2016) noted that long questionnaires can sometimes stress the respondents and lead to lack of motivation. These reasons lead to alternative approaches for personality assessment in a subconscious way. At the same time, concerns have arisen regarding the potential impact of e-learning methods on the authenticity of the student-teacher relationship. In their study, (Kim, Lee and Ryu, 2013) investigated the impact of personality on e-learning performance and proposed a user framework to enhance adaptable e-learning systems. Their findings suggest that extraversion may affect the ease to perform a learning task in an e-learning environment. In previous studies, a personalized game lead in reduction of cognitive load and mental effort within the game (Tlili et al, 2019), also learning motivation can be

enhanced if personality type is taken into account in the game (Hwang et al, 2012). In our study we developed an educational game as an approach to gather data such as subconscious moves, choices, and behaviors exhibited during the gameplay and then utilize data classification algorithms to measure the players' personality. An extension of this approach would involve providing this valuable data to game designers and educators for more personalized instruction.

The rest of the paper is structured as follows: Next section presents the background and related work to the current study. In Section 3 the educational game is described and the conducted experiment to evaluate it is presented. In Section 4, the methodology used is explained. Section 5 details the classification algorithms and the results, and finally, Section 6 concludes with limitations and future directions.

2. Background and Related Work

Several studies have explored whether individuals with similar personalities tend to exhibit similar preferences for game genres such as adventure, shooting, puzzle, and simulation games (Fang and Zhu, 2011; Peever, Johnson and Gardner, 2012; Dewanto and Tiatri, 2021). Fang and Zhu (2011) assume that it is likely that players choose games that align with their own extraverted personality traits. Additionally, research conducted by Tili et al (2019) has examined whether a personalized game based on the players' personality may impact their engagement and cognitive load. Various game mechanisms such as scoring, feedback and difficulty, have been investigated for their influence on players' motivation. This study also examined the influence of this game personalization on technology acceptance. Players who used the personalized game expressed more positive feedback regarding its perceived usefulness and their intention to continue using the game in the future (Tili et al, 2019).

Prior studies also examined the violent behaviours in video games and the potential to indicate violent personality. It appears that the players having more aggressive personality, act more violent while playing as well (shooting, kicking etc)(Peng, Liu and Mou, 2008). A meta-analysis showed that the exposure to violence in video games is related with aggressive behaviour, desensitization, and dearth of empathy (Anderson et al, 2010). While numerous studies have centred on game genres or violent video games, our research takes a distinct approach by focusing on investigating individual player behaviours and choices within games as potential indicators of personality characteristics.

The OCEAN Big Five Model (John, Naumann and Soto, 2008) is a popular model that assesses five personality traits that is also known as Five Factor Model. The OCEAN is an acronym that represents the five personality factors: Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism. According to the model, people scoring high on extraversion are more likely to exhibit sociability and are driven with positive emotions and energy. On the other hand, individuals with high Openness to Experience tend to be curious, imaginative, and have artistic interests. The Big Five Inventory (BFI) questionnaire (John et al, 2008), is a widely used self-report assessment that consists of 44 questions. The statements of the questionnaire are referring to a specific trait. The respondents are asked to choose how much they relate to each statement by rating in a Likert scale. According to the given rates a score is calculated and the respondent's personality is determined.

In the past years, research has been conducted to model personality with games as an alternative method. Denden et al (2018) developed a computer architecture educational game to measure learners' personality and ran an experiment with thirty-four University students. The BFI and TAM models were employed to measure personality and technology acceptance respectively (Denden et al, 2018). By utilizing the Naive Bayes classifier and collecting gameplay data, the researchers modelled personality traits. This study focused on extraversion and openness to experience and the predictions for both factors had high accuracy compared to the respective BFI scores. Afroza et al (2021) developed a 3D game that serves as a psychometric tool measuring extraversion, neuroticism, and conscientiousness. Pearson's correlation was used between the scores of the BFI and predicting values. The results showed that neuroticism had a moderate correlation while the extraversion and conscientiousness results were not satisfactory. In addition, a study that aimed to identify the conscientiousness trait using an Item Response Theory system (Palhano, Machado and Almeida, 2020) gave encouraging results. Specifically, the variables of the game regarding the conscientiousness were related with the respective variables of the BFI. Finally, research by Shen et al (2012) used text analysis, behavioural and social network data to infer personality. The study involved more than one thousand participants and the results indicated that the character and guild names hide valuable personality information.

3. The Case Study

3.1 The Game Development

The game was developed in Unity, a free, strong, and well-known tool for game development. In Unity both 2D and 3D games can be developed while it is also widely used in 3D animations (VR and AR development). It allows the development of serious games running in multiple platforms (mobile devices, desktops) concurrently. This game targets Windows and Linux Operating Systems for desktop usage, ensuring a user-friendly downloading and installation process. Scripting in C# helps in building stable and custom applications. The game's design, development, and testing process lasted approximately four months.

3.2 The Game Concept

Designed as an interactive quiz experience, UniGame aims to strengthen the knowledge and comprehension of Databases subject among university students. The Database course is a mandatory component of the curriculum. The game presents a virtual university environment where players freely navigate through different rooms as shown in Figure 1, asking a task to the user. When the task is completed, a quiz question related to Databases is showing up in Greek. Greek is selected as the native language of the students for better comprehension. Since feedback is an essential characteristic of the learning process, a positive or negative feedback is given, based on the answer given for the specific quiz question. Figure 2 depicts the positive feedback provided when players select the correct answer. The primary objective of the game is to collect valuable behavioural data in order to model the learner's personality. The game gathers additional data regarding the learning process and student responses to the game questions. Future data analysis took place to assess whether the gathered data are sufficient to provide meaningful insights about user personality traits. The data gathering is restricted to two personality traits: Extraversion and Openness to Experience. The data collected from the game regarding the Databases course can be analysed to identify patterns in student responses and areas of weakness.



Figure 1: Screenshot of the map of the game

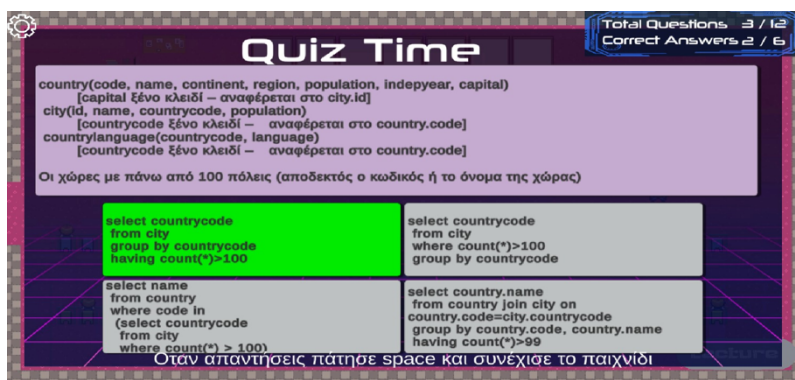


Figure 2: Screenshot of the quiz game when the selected answer was correct.

3.3 The Game Design

The primary objective behind designing the educational game was to collect relevant data effectively. The selection of the game environment along with the details of every room are all important indices of the personality. All the freedom given to the player, the user interface, and the game functionality were designed to be used in the predictions. The rooms and the map of the game are tile-based with multiple levels of tiles. The educational quiz component was designed to offer an optimal user experience and gain high knowledge retention. As mentioned above the player could freely navigate in the university and choose the rooms they wanted to visit as many times as they wanted. This gives them freedom and gives us information about the room visits.

Sociability and enjoyment of social interactions serve as indicators of extraversion, while feelings of loneliness are often associated with introversion (John, Naumann and Soto, 2008). In two rooms of the university the player is asked to choose where they will take the class. The two choices were: a chair surrounded by other students and a chair to sit alone. Additionally, since individuals high in openness to experience are driven by curiosity and a desire for novel experiences, exploring different locations within a game can be used as a measure of this trait (John, Naumann and Soto, 2008). Curiosity and desire to explore new areas is measured by the players' visiting choices. Extraversion is measured with colour preferences for avatar and selections in the game. According to research conducted in the USA, extraverts tend to prefer warm colours while introverted people tend to prefer cool colours (Choungourian, 1967). While Jia et al (2016) suggest that extraverts are more likely to find leaderboards enjoyable and beneficial as compared to introverts. This is why the leaderboard was also added to the initial game settings. Since studies found that there is a significant correlation between openness to experience and academic results, knowledge, and overall school performance (Ackerman and Heggestad, 1997; Farsides and Woodfield, 2003), the final score of the quiz is a trace too. Research suggests that individuals with introverted personalities are more susceptible to distraction when it comes to music and background noises, particularly during cognitive activities or work (Furnham and Bradley, 1997; Dobbs, Furnham and McClelland, 2011). Music and sound effects were integrated into the initial settings of the game to measure extraversion. Last but not least, people with low openness to experience are less likely to prefer art and in particular abstract art compared to the high openness individuals, who exhibit greater artistic and aesthetic inclinations (Feist and Brady, 2004; Chamorro-Premuzic et al, 2009). Thus, visiting the art room multiple times may be a trace indicating high openness and the painting they choose could also be a predictor.

3.4 The Participants

The study was conducted at a Computer Science Department offering an opportunity for all enrolled students in the database course to participate. The study aimed to include students from various academic levels. To encourage participation, a 0.5 bonus motivation was offered to those successfully passing the final exams. Out of the 174 students who initially expressed interest in participating, a total of 149 students actively engaged in the survey and completed all required procedures.

3.5 The Procedure

Throughout the procedure, a Zoom call was conducted to supervise and assist the participants. Any queries or difficulties encountered during the game installation and execution were addressed and resolved. The students were required to download and play the game, and then upload the generated files to the University's e-learning platform. The final step involved completing the BFI questionnaire in Greek.

4. Methodology

The behavioural data along with the BFI questionnaire for each student were pre-processed and merged into two datasets, each aimed at predicting a specific personality trait. The resulting datasets were formatted to be compatible with Pandas Library to run the classification algorithms in Python. The Pandas library was utilized to handle the dataset, while the scikit-learn library was employed for machine learning algorithms and metrics. The dataset consisted of a total of 21 variables, as shown in Table 1.

Table 1: The Variable values | Opposite Variable values of the dataset

Variable value	Opposite Variable value	Type
Blue avatar	Red Avatar	Numerical integer
Leaderboard Enabled	Leaderboard Disabled	Numerical integer
Music On	Music Off	Numerical integer
Sound Effects On	Sound Effects Off	Numerical integer
Canteen blue chair selected	Canteen red chair selected	Numerical integer
Lab Alone	Lab with others	Numerical integer
Lecture Alone	Lecture with others	Numerical integer
Visited Lib	-	Numerical integer
Art Room Abstract Painting	Art Room Classic Painting	Numerical integer
Visited All Rooms	-	Boolean
Successful game	Game Over	Numerical integer
Final score	-	Decimal number

The “Visited all rooms” becomes true when the player has visited all the rooms within the game environment. Game run is considered as successful when six or more questions are answered correctly. The “Final score” indicates the score achieved in the last played game. The remaining variables mentioned above are integers, representing the total count of occurrences for each variable within the different runs. The 22nd variable was the class of each personality trait (Extraversion or Openness to experience) that we aimed to predict. The scores served as Ground truth. The BFI score is calculated by reversing the scores of the negative questions and then averaging the scores of the questions related to each personality trait. The resulting mean falls within a range of 1 to 5, with values between 1 and 3 categorized as "low" and those between 3 and 5 classified as "high." For extraversion 69 students were categorized as having a “low” score and the remaining students were labelled as “high”. As for openness to experience, 73 students were labelled as “low” and 76 as “high”.

5. Results

The generated datasets of the collected and pre-processed data were utilized to run the classification algorithms and predict the class for Extraversion and Openness to Experience. For model evaluation, a 20-80% test-train split was employed on the data. The train set was used to run the classification algorithms and make predictions on the test set. Experiments with four algorithms: Naive Bayes Classifier, Decision Trees, k-Nearest Neighbour (k-NN) and Logistic Regression for 15 different seeds were conducted. Their performance was evaluated using Accuracy, Cohen's-Kappa, F1 score and AUC-ROC curve metrics. The accuracy metric is defined as the proportion of the instances that were correctly classified out of the overall instances. The Cohen's-Kappa measure is evaluating the agreement between two raters considering the factor of chance. F1 score (also known as F-score) evaluates the model performance by combining the precision and recall values. Finally, a high AUC ROC metric suggests that the classifier performs well at distinguishing between the classes. The optimal algorithm, along with the respective results of all metrics, is detailed in Table 2.

During the game, continuous music played in the background, while the sound effects provided positive or negative feedback to the player. These audio elements were collected for their potential impact on extraversion. As noted above, previous research has shown that music may distract individuals during cognitive activities. However, the sound effects are used to notify the players about the correction of their responses. The majority of the players retained the sound effects on during gameplay, minimizing their potential impact on extraversion. In addition, after several runs it was observed that certain variables had a negative impact on the results, leading to lower scores in the evaluation metrics. This happened specifically for the extraversion predictions, this is why the “Game Over”, “Sound-on”, and “Sound-off” variables were excluded from the dataset in the final experiments.

In our study, we evaluated the performance of our model in predicting the Extraversion, achieving an accuracy score of 0.7 and a Cohen's Kappa agreement of 0.4 (as shown in Table 2). A similar study conducted by Danden et al (2018), where they worked with forty four participants, including 34 learners who played the game and completed the BFI questionnaires. In their study, the BFI scores were categorized into "low", "balanced" and "high" classes for both Extraversion and Openness to Experience personality traits. Due to a limited number of observations in the "balanced" category (2 for Extraversion and none for Openness to Experience), we decided to simplify our analysis to two classes, as discussed in Section 4.

Danden et al achieved a score of 0.79 in accuracy and a Kappa agreement of 0.65 using the Naive Bayes algorithm. While this accuracy is higher compared to our model, it can be attributed to the disparity in sample sizes. The above findings identify areas of improvement in our model, for instance we acknowledge the need to collect additional traces, such as risk factor and players' emotional states as done in Danden's study.

When it comes to Openness, our model achieved an accuracy of 0.73 and a Cohen's agreement of 0.45 using the Naïve Bayes algorithm. Notably, our accuracy is slightly higher than that on Danden's et al study (0.70) when using the same algorithm. This result is encouraging, particularly considering the broader sample size of 149 players in our study, enhancing its generalizability. However, it's worth noting that there is room for improvement in terms of the Cohen's Kappa value. The values of F1 score and AUC-ROC are satisfactory across both personality traits. The results of the Afroza's et al (2021) study on extraversion did not show correlation with the ground truth data; this is why we do not proceed to comparisons.

Table 2: The evaluation metrics of the classification algorithms for each personality trait

Personality Trait	Classifier	Accuracy	Cohen's-Kappa	F1 score	AUC-ROC
Extraversion	Logistic-Regression	0.7	0.4	0.76	0.64
Openness	Naive Bayes	0.73	0.45	0.64	0.76

6. Conclusion, Limitations, and Future Directions

In recent days, educational games have gained recognition and are widely used, while personalized games based on personality or educational level are a subject of research that shows great promise. Our game offers the potential to collect data in a subconscious way, to identify some personality traits. The moves, choices and behaviours exhibited in a game can be used as indicators to model personality. A future direction is to adapt the game to match the individual's personality. In this way, the educational process can be optimized, resulting in improved knowledge retention. Our model performs effectively on extraversion and openness traits, but further enhancements are required, particularly in improving the Cohen's Kappa metric. In related studies, a smaller number of participants were involved, and they utilized only a single algorithm. The difference between the values of the previous studies and our model may lay in the difference in the size and motivation of the sample.

Several limitations emerged during the study that could have influenced the results concerning the gameplay procedure. It should be noted that during the zoom call students frequently asked questions about the gameplay, indicating a lack of caution to the game guidelines. It can be inferred that the students' primary motivation was to complete the process to receive the bonus for the course. Additionally, it was observed that many students were unexpectedly quitting the game before reaching its conclusion, without any reason for doing so. This possibly indicates a lack of thorough reading of the instructions or unfamiliarity with the quiz questions. At the same time, some students appeared determined to continue playing until they successfully completed the game, disregarding the instruction to play it only once. All the above may have a negative influence on the reliability of the gathered data.

Future research contains the data analysis of the quiz answers, the identification of patterns in the responses. An area that holds significant interest is the expansion of this educational game in personalized educational game. Through this extension we would aim to explore the relationship between learning outcomes in higher education and two distinct types of quizzes: personalized game quizzes and non-game quizzes. The relationship of educational data analysis with personality is an area of particular interest. Since the psychological part of the game is based on literature research, future research in collaboration with psychologists for the collected data is required to optimize the results.

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