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EDUCATIONAL GAME TO MODEL LEARNER’S PERSONALITY

A dissertation
by

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EDUCATIONAL GAME TO MODEL LEARNER'S PERSONALITY

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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. 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 thesis, an educational game focused on Databases courses for university students was developed. 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 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 (Naive Bayes Classifier, Decision Trees, k-Nearest Neighbour (k-NN) and Logistic Regression) to develop a model to predict students' 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 considering the learner's personality and thus provide valuable insights for future research in this domain.

Keywords: Educational game, Gaming behaviour, Gameplay, Personality, Classification

Foreword – Special thanks

I would like to express my sincere gratitude to Professor Mr. Maria Aikaterini Satratzemi for our collaboration and her constant help in questions and problems that arose during the study. Additionally, I extend my thanks to the professors of the Databases course, Mr. Evangelidis Georgios and Koloniari Georgia, for providing the educational material utilized in the game. I would also like to express my appreciation to the university students who participated in the survey. Their participation greatly contributed to the completion of this research. Special thanks are extended to my friends and family for their constant support and encouragement.

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Acronyms

OCEAN- Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism

BFI - Big Five Inventory

TAM- Technology Acceptance Model

FFM – Five Factor Model

k-NN – k-Nearest Neighbour

1 Introduction

1.1 Problem – Importance of the topic

Digital devices have become ubiquitous in almost every house, with both children and adults using them for online services, education, entertainment, and communication. While early examples of video games date back to the 1950s, the games of the 21st century have evolved significantly, becoming highly immersive and engaging. The popularity of video games has witnessed a remarkable increase, with games becoming an indispensable and integral part of people's lives. An emerging type of video games are the educational ones that combine both educational and entertaining elements at the same time.

Various studies have been conducted with the aim to explore the relationship between gameplay and players' psychology. Some studies focus on specific game genres (Dewanto and Tiatri, 2021) while others examine the particular behaviours exhibited by players during gameplay, which may be associated with their individual personalities. A common way to measure personality is through questionnaires in a self-report form. The Big Five Inventory (BFI) is probably one of the most popular questionnaires for personality (John et al., 2008). 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, such as educational games.

At the same time, concerns have arisen regarding the potential impact of e-learning methods on the authenticity of the student-teacher relationship and the tutor's ability to accurately gauge the current status in their classes. In their study, Kim et al., (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 led to reduction of cognitive load and mental effort within the game (Tlili et al., 2019). Learning motivation can be enhanced if personality type is taken into account in the game (Hwang et al., 2012). We suggest that educational games hold the potential to collect data during the gameplay, utilize data algorithms to assess players' personality, and dynamically adapt to individual learners. This approach promises to bring satisfaction to both students and educators, as it enables instructors to deliver highly personalized instruction.

1.2 Aim – Objectives

As part of this thesis, an educational game tailored for university students has been developed. The primary objective of the study is to explore the potential of predicting the levels of two personality traits of the OCEAN model (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism), namely Openness to Experience and Extraversion.

According to the OCEAN model, extroverts are typically social and are characterized by their inclination towards positive emotions and high energy. Individuals with high Openness to Experience tend to be curious, imaginative, and have artistic interests. Given the distinctive features associated with Extraversion and Openness to Experience these personality traits have been selected as the primary focus of our investigation.

It is worth noting that these specific personality traits had substantial attention in prior literature and have been the subject of numerous empirical studies. This enables meaningful comparisons and increasing the understanding of these personality traits within the educational games.

To evaluate personality, data are gathered from various aspects of gameplay, including socializing interactions and specific choices made by the players. It is important to note that the implementation of this thesis strictly adheres to scientific purposes and does not undermine the significance of the field of psychology. Some classification algorithms are employed to predict the levels of extraversion and openness to experience based on the collected data. To assess the actual levels of the aforementioned personality traits the BFI questionnaire is employed and used as ground truth. Various metrics were employed to assess the model and enhance the generalizability of the findings.

The developed educational game has a primary goal of enriching students' comprehension and knowledge of the challenging and demanding subject of Databases, which often elevates stress levels among university students. However, it's essential to emphasize that Databases holds significant importance within the academic curriculum. Achieving a deep understanding of Databases is vital, even when the material appears complex. This game serves as a mean to simplify and make the learning of databases more accessible and enjoyable.

1.3 Contribution

The contribution of this study lies in its focus on data analysis within the context of an educational game specifically designed for university students. This game captures daily behavioural patterns observed in players' lives within the university environment. One key novelty of the game is its potential to be adaptable in multiple subjects, allowing for customization of quiz questions and answers across various fields of study. Additionally, the game collects player responses to provide valuable feedback to tutors regarding the educational progress of their class. By utilizing machine learning techniques, algorithms, and metrics, the study also aims to predict players' personality traits, enhancing our understanding of the intersection between gameplay and individual characteristics.

Future contribution of this study includes taking advantage of these predictions to elevate a common educational game to a highly personalized level. Personalization in games increase players' engagement and immersion. Furthermore, this customization extends to the educational content itself, aligning it with the unique personality traits of each student. Personalization within games can further extend in terms of the educational context according to the knowledge acquired by each individual learner.

1.4 Basic terminology

OCEAN- Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism

BFI - Big Five Inventory

TAM- Technology Acceptance Model

FFM – Five Factor Model

k-NN – k-Nearest Neighbour

1.5 Structure of the study

The current Chapter refers to the aim and contribution of the study. Theoretical background of video game and game engines and literature review are presented in

Chapter 2. Chapter 2 also discusses previous research on similar subjects. The Chapter 3 presents the methodology followed to measure learners' personality, specifically the game developed in the context of this thesis, the followed procedure in the case study, and the results. In the Conclusion chapter the summary, research limitations and possible future extensions are detailed.

2 Background – Related work

2.1 Video Games

The main purpose of games has always been entertainment. Over the years games have changed form, and today probably the most popular form of games are video games. According to Zyda, (2005) "video games require the use of electronic devices, aiming to entertain and amuse the players, following some predefined rules" (Zyda, 2005). Video games produce visual feedback according to the user's interaction with an electronic device. Video games are commonly classified based on their hardware platform, with the traditional categories including arcade video games, console games, and computer (PC) games. LAN games, online games, and browser games are also included within the category of PC games. Nowadays, the video game industry has grown in various platforms, including mobile gaming on devices like smartphones and tablets, virtual and augmented reality systems, and remote cloud gaming. Additionally, video games are categorized into numerous genres based on their gameplay style and intended audience.

2.1.1 Educational Games

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 as they are attractive and engaging. Serious games' main objective is to strike a balance between entertainment and interactive education (Noemí and Máximo, 2014). Unity allows the development of serious games running in multiple platforms (mobile devices, desktops) concurrently. Additionally, HTML5 is a programming environment designed for building games that can be accessed from web browsers, ensuring universal accessibility. The above-mentioned tools are highly suitable for the development of serious games (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).

2.1.2 The Benefits of Video games and educational games

Video games have several benefits, including skill development, as emphasized by education speaker Marc Prensky. For instance, players learn to focus on a desired target and handle situations where multiple events occur simultaneously (Prensky, 2003). Children playing video games develop the ability to infer and derive the rules of a game based on the information they observe. The player in order to win usually has to multitask, create and follow specific strategies. Playing games also enhances skills like effectively assimilating information from various sources (Prensky, 2003). In addition, playing educational game players increases player 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. Additionally, the significance of feedback is highlighted by Lieberman et al (2014) as players continuously receive assessment of their skills and tasks. Furthermore, feedback helps players maintain focus on their goals, leading to higher levels of motivation and engagement (Garris et al., 2002).

2.2 What is a game engine

The widespread popularity and utilization of video games have necessitated the development of game engines, enabling easier development and maintenance of video games. A game engine is the software development environment used to create video games. Physics, user input, 2D or 3D rendering, coding and artificial intelligence are some of the features combined to develop more advanced video games. The major advantages of game engines include making it easier to handle technical details, testing games repeatedly, and supporting numerous platforms and software ("Game engine," 2023). Game maker, Unreal Engine, and Unity are some of the most well-known and effective game engines.

2.3 Unreal

Unreal Engine is one of the most widely used game engines in the world, supporting both 3D and 2D games. It is more frequently used for 3D games ("Unreal Engine," 2023). It was created by Epic Games in 1998, and it's increasingly gaining popularity. Unreal Engine games can run on various platforms such as desktop, mobile, consoles, virtual reality devices. It is more frequently used for 3D games and employs

C++. One of the greatest advantages of unreal engine is its high-quality graphics while it supports real-time lighting, dynamic shadows, advanced materials, and textures. You can utilize Unreal Engine without any cost to create linear content such as films, as well as for custom and internal projects. For game development when less than $1 million USD is earned it is also free ("Game Engine | Build Multi-Platform Video Games - Unreal Engine," n.d.). Fortnite, a multiplayer survival, battle-royale game (Epic Games, 2017) and Hellblade: Senua's Sacrifice, an action-adventure single player game were created with Unreal Engine (Hellblade, n.d.).

2.4 Game maker

GameMaker (also known as GameMaker Studio) is a cross-platform game engine that was first introduced in 1999 ("GameMaker," 2023). It provides a customized drag-and-drop programming language and the Game Maker Language that requires scripting. Using the above-mentioned languages, developers can create simple and more advanced games. Video games developed in Game Maker can be deployed on Windows, Mac, Linux, Android, iOS, HTML5, Xbox, PlayStation, and Nintendo Switch. It supports mostly 2D games and gives limited 3D graphics capabilities. GameMaker offers both free and paid versions ("Game Maker Official Website," n.d.).

2.5 Unity

Unity is a multi-platform game engine first released in 2005 for Mac OS X. Microsoft Windows and Web browsers were supported afterwards as well as mobile (Android and iOS), Virtual Reality and console platforms. In Unity both 2D and 3D games can be developed while it is also widely used in 3D animations (VR and AR development). Unity Personal is free for non-commercial use or commercial use with annual revenue of less than 100K$ ("Unity (game engine)," 2023). Except for video games, Unity engine is also used in the film, architecture, and construction industry.

Several reasons why Unity is widely used are its ease of use and its large community. The latter offers extended documentations and tutorials, while plenty of tutorials are also available on the web. In addition, searching in the Unity forums can give answers to specific questions and problems. When it comes to the ease of use, unity offers a built-in feature (drag and drop functionality) that simplifies video game development.

The Unity Asset Store is a valuable resource for game developers that was launched in 2010, offering an abundance of free and paid 2D and 3D assets, audio, and tools. Physically based rendering and global illumination, further enhance the potential of these assets and allow the development of more valuable games. Additionally, the Unity Asset Store is a collaborative effort, featuring assets created by both Unity Technologies and the large Unity community, offering a diverse library of textures, animations, tutorials, and whole projects. Last but not least, the physics engine and scripting API allows developers to build high-quality games.

Unity also provides unity analytics to monitor the performance of the game and playing behaviour in an easy on the eye way (line and bar charts) ("Game Insights & Analytics Dashboard Software | Unity," n.d.). Total Days Played and average minutes (AVG Mins) Played per Session Last 7 Days are sample metrics that measure the overall impact of the game. These metrics are involved in unity analytics and no need of configuration, while custom events can be used to track more specific actions if needed. Download and implementation of SDK is necessary to create custom events. Event Manager and Event Browser are tools to view/handle and troubleshoot all the events respectively. Three dashboards are provided to measure game performance, retention and revenue and can be filtered by country, version, platform, and audience. Some analytics such as daily new users, daily active users, and session length are given in charts. Data explorer provides refined data visualization and is used to group and filter data and events. All these analytics are important to measure in-game behaviour and proceed to changes in the game in case of intervention.

Unity has many powerful features for mobile games and is preferred for 2D content because of its well- developed 2D tools. Some popular games developed in Unity are Among Us, Pokémon Go and Cuphead. Taking into consideration all the above-mentioned tools that Unity provides, it is chosen as the game engine for the educational game developed in this project.

2.5.1 Scripting in C#

Unity engine uses a scripting API in C# and Mono (“Mono (software),” 2022). Mono was implemented by Microsoft's .NET Framework in 2004, it is also free to use and open source. C# ((pronounced "See Sharp")) is an object-oriented programming language that first appeared in 2000. Its applications run in .NET, a free, open source and fast cross platform framework that is compatible with Windows, Linux, and Mac OS (.“NET | Free. Cross-platform. Open Source.,” n.d.). C# is based in C, consequently it is easy to use for C, Java, and C++ developers. Using C# helps in developing stable and secure applications. C# can be characterized as a high-level powerful and efficient language with improved runtime performance. It is used in various applications such as desktop and web applications and game development. Garbage collection, lambda expressions, error detection and exception handling are some C# features (BillWagner, 2022).

2.6 OCEAN, BFI and Personality traits

The OCEAN Big Five Model (John et al., 2008) is a popular model that assesses five personality traits that is also known as FFM (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.

There is an abundance of psychometric tools that measure personality traits, the Big Five Inventory (BFI) (John et al., 1991) is probably one of the most widely used questionnaire. Specifically, the BFI is a self-report measure developed by John, Donahue, and Kentle in 1991 that consists of 44 short, simple questions. It is crucial that each question is straightforward eliminating any potential confusion or ambiguity for participants. As the name suggests, the BFI focuses on the "Big Five" personality traits: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. 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 5-point Likert scale where 1 represents “disagree strongly” and 5 represents “agree strongly”. This scoring system allows for the calculation of an average score for each trait, enabling the questionnaire to measure individual traits separately. It appears that openness to experience is strongly associated with extraversion and vice versa (Farsides and Woodfield, 2003). Extroverts are generally characterized as sociable, energetic, and positive individuals, whereas those with high openness scores tend to be curious, imaginative, and have a need for variety (McCrae and Costa, 1989). Based on the scores on each personality trait classes of each trait were created.

2.6.1 Indicators of Extraversion and Openness to Experience

In the context of measuring these personality traits, various factors have been employed as indicators or traces. Sociability and enjoyment of social interactions serve as indicators of extraversion, while feelings of loneliness are often associated with introversion (McCrae and Costa, 1989). 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. According to research conducted in the USA, extraverts tend to prefer warm colors while introverted people tend to prefer cool colors. In addition, it appears that male exhibit a high preference for warm colors compared to females (Choungourian, 1967). In another similar study, there was statistical significance between sociable, outgoing individuals and saturated colors (Compton, 1962). Red is considered a saturated color. As mentioned above, being sociable is a characteristic of extraversion. The results of another study showed that there exists a significant correlation between high scores in extraversion and a strong inclination towards scoring systems, level progression, and leaderboards in gaming (Jia et al., 2016). This study indicates that individuals with higher extraversion tend to derive more enjoyment and perceive greater usefulness from leaderboards compared to their introverted counterparts. The above findings highlight the influence of personality traits on individuals' attitudes towards gaming metrics, suggesting that extraverts are more likely to find leaderboards enjoyable and beneficial as compared to introverts (Jia et al., 2016). Various 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). Interestingly, this particular trait emerged as the most noteworthy factor associated with academic success (Farsides and Woodfield, 2003). Ackerman and Heggestad (1997), also noted that there is no correlation between school performance and achievements and extraversion. 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 (Dobbs et al., 2011; Furnham and Bradley, 1997). Specifically, extraverts tend to maintain their performance levels even while listening to music or being exposed to noisy environments. In contrast, introverts experience declines in their performance scores under similar conditions. The above reasons resulted in giving the opportunity to the player to enable and disable the music and sound effects during the gameplay whenever they wanted. People with low openness to experience are less likely to prefer art and in particular abstract art compared to the high openness individuals (Chamorro-Premuzic et al., 2009; Feist and Brady, 2004). The findings of a study that took place in the United Kingdom with more than 91.000 participants showed that the degree of openness to new experiences emerged as the most influential and reliable predictor of artistic preferences (Chamorro-Premuzic et al., 2009). The authors highlight that individuals with a higher level of openness to experience exhibit greater artistic and aesthetic inclinations. Furthermore, high preference for impressionism is found to have a negative correlation with openness, while a preference for cubism is positively associated with openness (Chamorro-Premuzic et al., 2009).

2.7 Machine Learning Algorithms

Naive Bayes Classifier, Decision Trees, k-Nearest Neighbour (k-NN) and Logistic Regression are some of the most popular classification algorithms. Their performance was evaluated using Accuracy, Cohen's-Kappa, F1 score and AUC-ROC curve metrics. Python was used to run the classification algorithms, predict the personality traits, and calculate the measures.

2.7.1 Naive Bayes Classifier

The Naïve Bayes Classifier is a probabilistic classifier that utilizes Bayes theorem, under the assumption that each feature is independent based on its class. Classifying objects becomes more difficult in scenarios with numerous features and classes because estimating probabilities would demand a big number of observations. The Naïve Bayes classifier uses the “class-conditional independence” assumption, which means that the effect of a variable's value on a particular class remains unaffected by the values of other variables.

As abstractly defined from (Murty and Devi, 2011a) ,"*the probability model for a classifier is a conditional model*

$$P(C|F_1.........F_n)$$

over a dependent class variable C with a small number of outcomes or classes, conditional on several feature variables F1 through Fn.". The issue arises when the number of features is large or when a feature can take on a wide range of values, then it is not feasible to work with a model using probability tables. A modification of the model by using the Bayes theorem is:

$$P(C|F_1.........F_n) = \frac{p(C)p(F_1......F_n|C)}{p(F_1......F_n)}$$

2.7.2 Logistic Regression

Logistic Regression commonly referred to as the logit model, finds frequent application in tasks related to classification and predictive analytics. *"Logistic regression estimates the probability of an event occurring, such as voted or didn't vote, based on a given dataset of independent variables"* (IBM, n.d.). Given the probabilistic nature of the outcome, the dependent variable in logistic regression is confined to a range between 0 and 1.

In logistic regression, the odds, denoting the probability of success relative to the probability of failure, undergo a logit transformation. This transformation is also recognized as the log odds or the natural logarithm of odds. The logistic function, which encapsulates this transformation, can be expressed by the following mathematical formulas:

$$Logit(pi) = \frac{1}{(1 + exp(-pi))}$$

$$Ln(\frac{pi}{(1 - pi)}) = Beta_0 + Beta_1 * X_1 + \ldots + B_k * K_k$$

In this logistic regression equation, logit(pi) represents the dependent variable and x represents the independent variable. The beta parameter (coefficient) within this model, is typically determined using the maximum likelihood estimation (MLE) approach. This technique involves assessing various values of beta through multiple iterations to achieve the optimal fit for the log odds (IBM, n.d.). There are three types of Logistic Regression: Binary, Multinomial and Ordinal.

2.7.3 Decision Trees

“A decision tree is a tree where each non-leaf or internal node is associated with a decision and the leaf nodes are generally associated with an outcome or class label.” (Murty and Devi, 2011b). Each internal node evaluates some attribute values, leading to multiple branches or links. Each of these links is associated with a potential decision value, and these links are both distinct and collectively cover all possible scenarios. In essence, there is a link available for every conceivable situation.

Decision trees serve as valuable tools for evaluating various courses of action. In the case of a binary decision tree, each node presents a decision statement or a comparison to be made. From each node, there are two outgoing edges: one representing the outcome "yes" or "true," and the other representing the opposite outcome ("no" or "false").

Decision trees are also used for pattern classification. In this case, the tree-nodes represent the status of the problem when the decision is made and the leaf nodes give the class label of the classification rule.

2.7.4 K-Nearest Neighbor

The nearest neighbor algorithm finds and assigns the class label of the closest neighbor of a test pattern to it (Murty and Devi, 2011c). The k-Nearest Neighbor algorithm (kNN), finds the k- closest neighbors of the test pattern. The class label assigned to the test pattern is determined by the majority class among these k closest neighbors. Selecting the appropriate value for k has significant importance for the classification accuracy.

2.8 Metrics

The machine learning classification algorithms are evaluated with metrics that are briefly described below. It is important to use more than one score to ensure that a model is working appropriately.

2.8.1 Accuracy

Accuracy of a value is measuring the number of correct predictions made by a classification model. The accuracy metric is defined as the proportion of the instances that were correctly classified out of the overall instances. The accuracy ranges from 0 to 1, with higher values indicating better performance and 0.5 being representing the randomness in the predictions. It is important that accuracy is used with other metrics as it usually leads to misleading in imbalanced classes (Bressler, 2022).

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalNumberofPredictions}$$

2.8.2 Cohen's-Kappa

The Cohen's-Kappa measure is evaluating the agreement between two raters considering the factor of chance. Validity measures how accurate a test is, while reliability is the degree to which a model can reproduce similar results. The Cohen's Kappa values can be positive and negative in the range of -1 to 1, with zero meaning the randomness. The higher the value, the more the agreement between the raters (Kurtis, 2018).

2.8.3 F1 score

F1 score (also known as F-score) evaluates the model performance by combining the precision and recall values. The F1 score formula is: F-score = 2 * (precision * recall) / (precision + recall). The F-score value can be between 0 and 1, with 1 indicating the optimal performance. It is usually used to strike a balance between the precision and recall measures.

2.8.4 ROC curve

The last metric used in the evaluation of the game was the ROC (receiver operating characteristic) curve. This curve uses true positive rate and false positive rate. True Positive Rate (TPR) is a synonym for recall and is defined as:

$$TPR = \frac{TP}{TP + FN}$$

False Positive Rate (FPR) is defined as:

$$FPR = \frac{FP}{FP + TN}$$

The AUC is the acronym of Area under the ROC Curve (Figure 1) and measures a two dimensional area under the ROC curve in the range of (0,0) and (1,1) as shown in Fig 13. AUC measures the performance across all possible classification thresholds. The AUC values range from 0 to 1. A high AUC ROC metric suggests that the classifier performs well at distinguishing between the classes. (Google for developers, 2018)

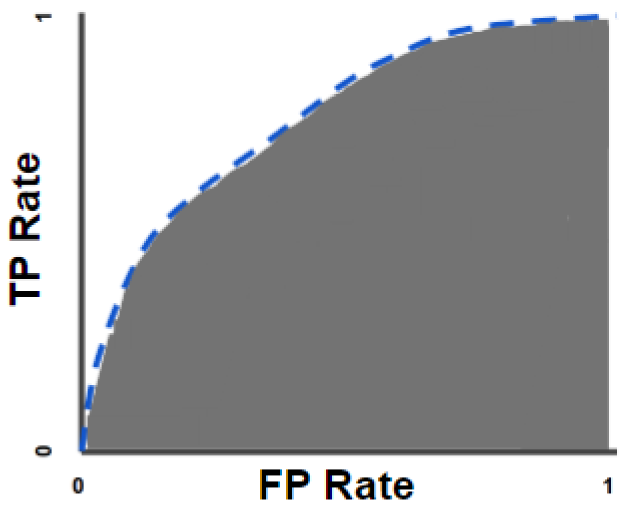

Figure 1 AUC (Area under the ROC Curve)

Source: [developers.google.com, AUC, 2018]

2.9 Related work

A substantial body of research has investigated the association between games and players' characteristics. 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 (Dewanto and Tiatri, 2021; Fang and Zhu, 2011; Peever et al., 2012). Fang and Zhu, (2011) assume that it is likely that players choose games that align with their own extraverted personality traits. The findings of a research by Dewanto and Tiatri (2021) showed that there is a correlation between Openness and Extraversion with sport games, with the latter showing a negative correlation with RPG.

Prior studies also examined the violent behaviours in video games and the potential to indicate violent personality. Forty undergraduates of the Midwestern

University took part in a survey that captured their screen video to examine if aggressiveness in violent games is higher in aggressive individuals (Peng et al., 2008). It appears that the players having more aggressive personalities, act more violent while playing (shooting, kicking etc) (Peng et al., 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).

Additionally, research conducted in Tunisia with fifty one undergraduate students, has examined whether a personalized game for teaching Certificate of Informatics and Internet (C2I) based on the players' personality may impact their engagement and cognitive load (Tlili et al., 2019). 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 (Tlili et al., 2019).

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 utilized accuracy and Cohen's Kappa metrics for the evaluation of the model. 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. In the survey thirty individuals participated and the evaluation of the game spanned a week. 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 et al., 2020) gave encouraging results. This survey included 29 participants that played the serious game and answered the BFF questionnaire and the General Health Questionnaire (GHQ). The variables of the game regarding the conscientiousness were related with the respective variables of the BFF. 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 (1040) and the results indicated that the character and guild names hide valuable personality information.

While numerous studies have centered 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.

3 Methodology

3.1 The Game

Designed as an interactive quiz experience, UniGame aims to strengthen the knowledge and comprehension of an introductory course on Databases among university students. The game presents a virtual university environment where players freely navigate through different rooms as shown in Figure 2. Each room offers a task to the user (Figure 3), when the task is completed, a quiz question related to Databases is showing up. Based on the answer given a positive or negative feedback is given and the player is relocated to the initial screen.

Figure 2 Map of the game

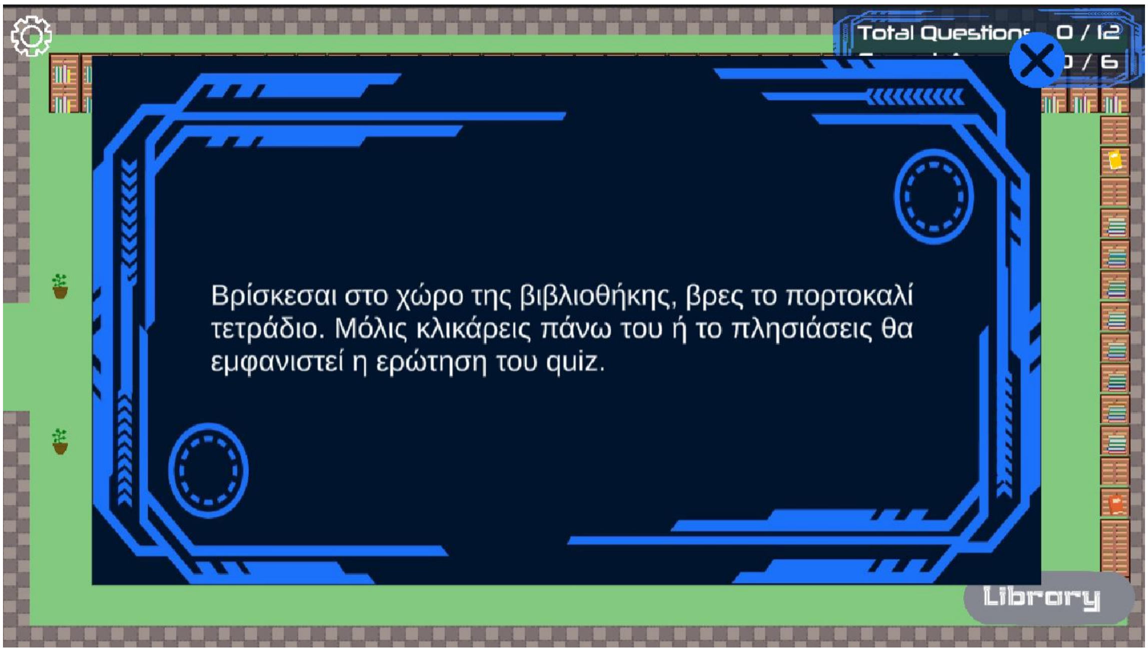

Figure 3 Specific task given in the library room.

The primary objective of the game is to collect valuable behavioural data in order to model the learners personality. The game gathers additional data regarding the learning process and student responses to the game questions. Future data analysis is taking place aiming 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 “Introversion-Extraversion” and “Openness to Experience”. As reported earlier, these two personality traits had earned attention in prior research and have been extensively examined in empirical studies (Denden et al., 2018; Tlili et al., 2019). This allows for valuable comparisons, contributes to a deeper understanding of how these personality traits operate in the context of educational games and extends the literature.

The data collected from the game regarding the Databases course can be analyzed to identify patterns in student responses and areas of weakness. This analysis provides valuable insights to tutors, enabling them to identify specific areas where students require further attention. By understanding which concepts may be unclear to students, tutors can focus their efforts more effectively and provide targeted support to enhance student learning in the course.

3.1.1 The Quiz

The quiz questions, consisting of a total of twelve, are provided by the professors of the Databases course. Each question offers four answer options, with only one being

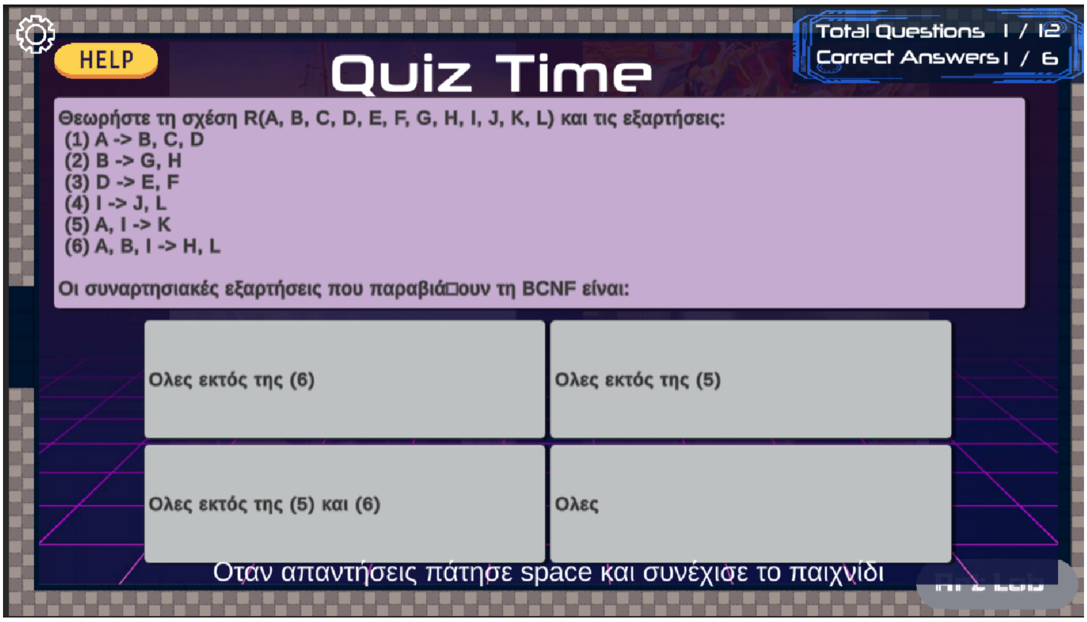

Figure 4 Quiz screen

correct. To maintain integrity, the sequence of questions presented to the players is intentionally randomized. This randomization serves multiple purposes. Firstly, it helps prevent cheating among university students who are simultaneously participating in the game. Secondly, it ensures the accuracy of student scores by minimizing the possibility of collusion. It is worth noting that the student scores will be used in our model.

The game incorporates a limited assistance feature where the player can use the 'Help' button shown in Figure 4 twice throughout the game. As depicted in Figure 5, pressing the 'Help' button deactivates two out of the four questions in that particular quiz question.

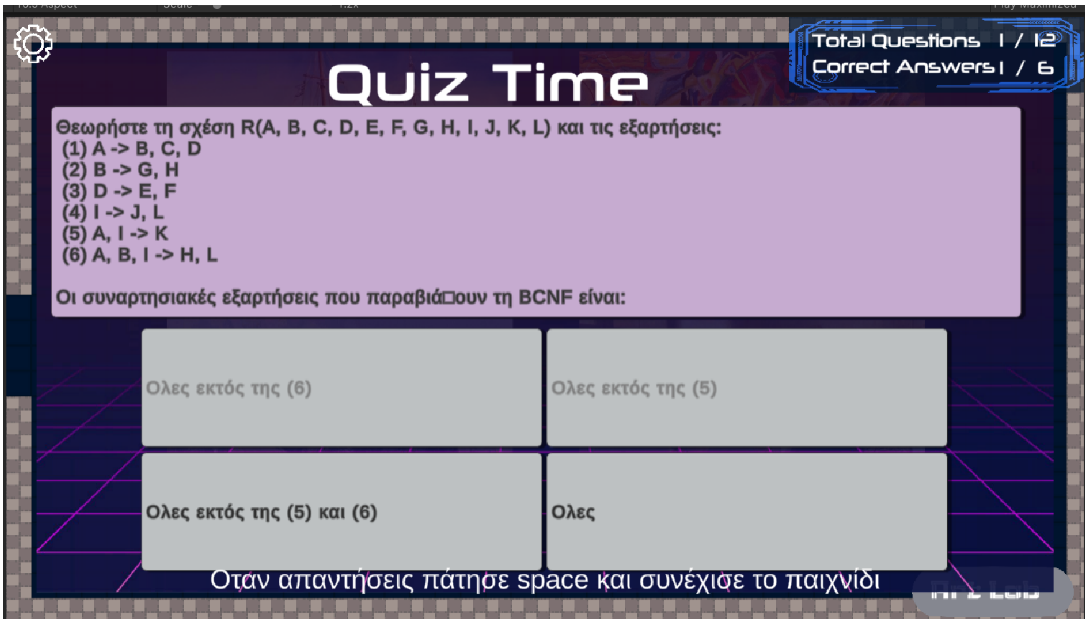

Figure 5 Quiz after Help is clicked.

When the player answers a question correctly, a positive sound effect is played, the correct answer is highlighted in green, and the UI score reflecting the number of correct answers is updated. All the above-mentioned updates are visible in Figure 6. However, if the player provides an incorrect answer, a disappointing sound effect is triggered, the selected answer is highlighted in red (Figure 7). As Figure 6 depicts the correct answer is displayed in green to allow the player to review it before proceeding.

By showing the correct answers, the game provides valuable feedback to the students, aiding in their learning and knowledge retention. This feedback mechanism enhances the educational value of the game and helps reinforce the understanding of the quiz topics.

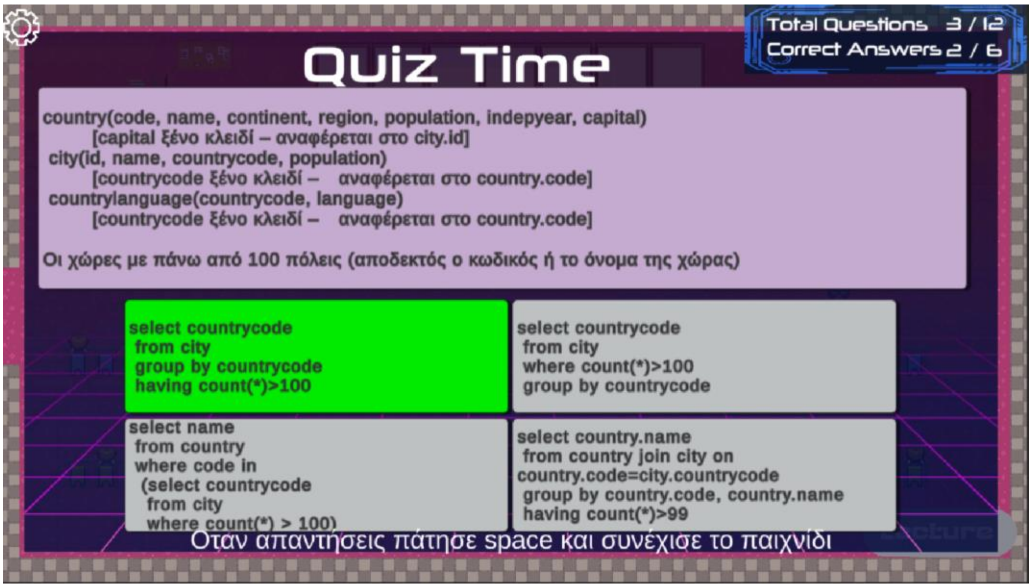

Figure 6 Correct answer selected

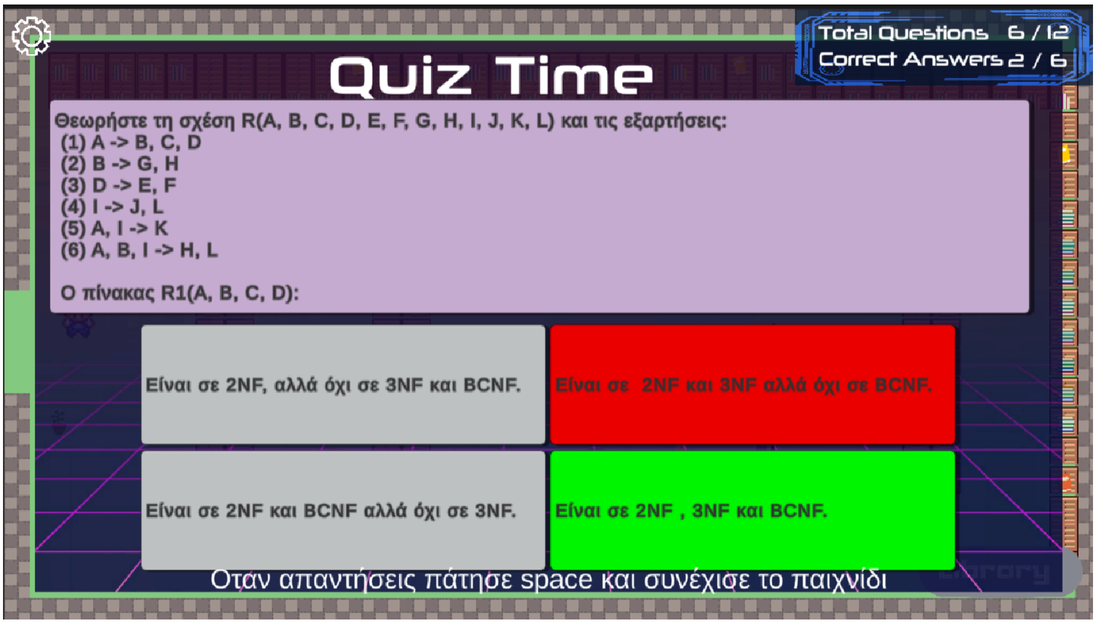

Figure 7 Wrong answer selected

Additionally, the student answers for each question are systematically collected, including the unique ID number of the student and the answer they provided. This comprehensive data collection enables the tutors to identify patterns in both correct and incorrect answers, facilitating valuable insights into knowledge retention and learning outcomes. By comparing the responses of individual students across similar questions, educators can infer whether the answers were randomly guessed or if the players genuinely understood the educational content. This analysis allows for a deeper understanding of student comprehension and provides valuable feedback for refining instructional approaches and enhancing the educational material.

3.2 The story

The main objective of the player is to answer the quiz questions displayed on the screen and successfully complete the game by answering at least six questions correctly out of the twelve. As previously mentioned, the player can freely navigate in the university map and select the room they want to visit. There are five rooms in the game: lab, art lab, lecture hall, canteen, and library. The player has the freedom to visit each room multiple times, and it is not mandatory to explore all the rooms. At the beginning of the game the player starts at the centre of the map so that they will choose a room according to their preference rather than rather than its proximity.

The "Lab" serves as a laboratory room where the player must select a chair to attend a course as shown in Figure 8. The player is presented with two options: one chair where they can sit alone and another where they will be surrounded by other university students. When the player approaches the chair, it is selected, and the quiz question is showing up.

Figure 8 Lab room

The 'Art Lab' serves as a repository for paintings, where the player is presented with a selection of four paintings to choose from (Figure 9). Upon selecting their favourite painting, the quiz is activated. It is important to note that during each visit to the room, the player encounters a unique set of four paintings (in total 16 different paintings throughout the game, Annex C. If the player revisits the room more than four times, the paintings will repeat a circle starting from the initial four paintings. Among the four paintings presented in each visit, one is abstract art, while the remaining three follow a classic style.

Figure 9 Art Room

The “Lecture Hall” follows the same philosophy as the lab, where the player must decide whether to sit alone or with others. The player's starting location is strategically placed so that the proximity to each chair is equal, providing a fair choice for the player.

In the "Canteen," the player is faced with a choice of where to be seated between two chairs positioned in the centre of the room. Notably, the table in the middle of the room is empty and comprises two chairs of different color: one chair is blue, and the other is red. This setup allows for the collection of information regarding the player's color preferences. This is an extra trace in the initial collected information of the avatar color.

When moving on to the "Library room," the player is tasked with locating the orange notebook, which is displayed in the bottom right corner of the screen (Figure 10). As the player clicks on or approaches the notebook, a quiz question will be presented to them.

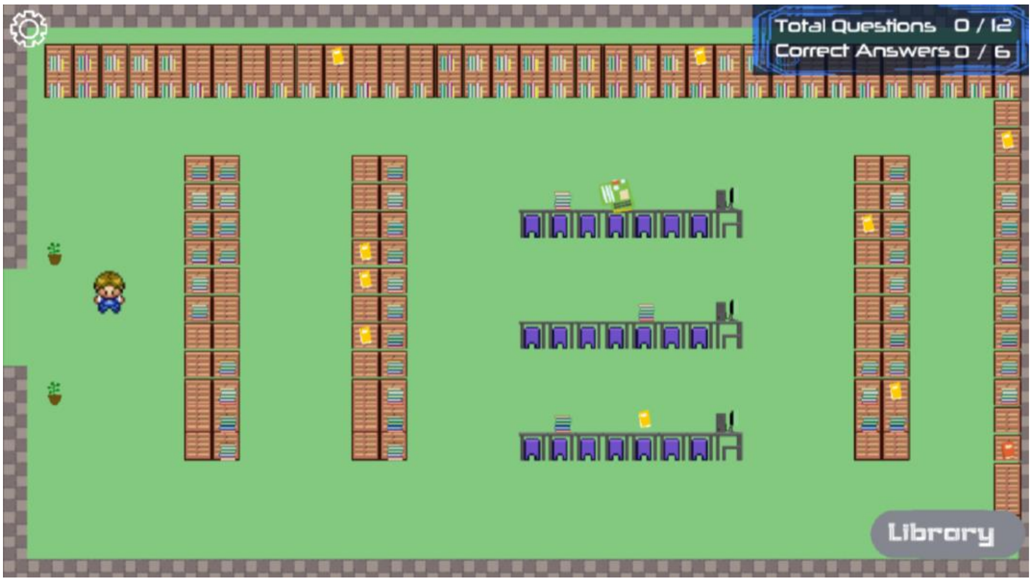

Figure 10 Library Room

Upon reaching the completion of the quiz, two distinct outcomes are possible. If the player has answered a total of 12 questions, the game concludes and transitions to the Game over screen. Alternatively, the player is directed to the Congratulations screen that displays the number of correctly answered questions in relation to the total number of questions the player has responded to thus far. This screen is depicted in Figure 11 and provides a sense of achievement within the game.

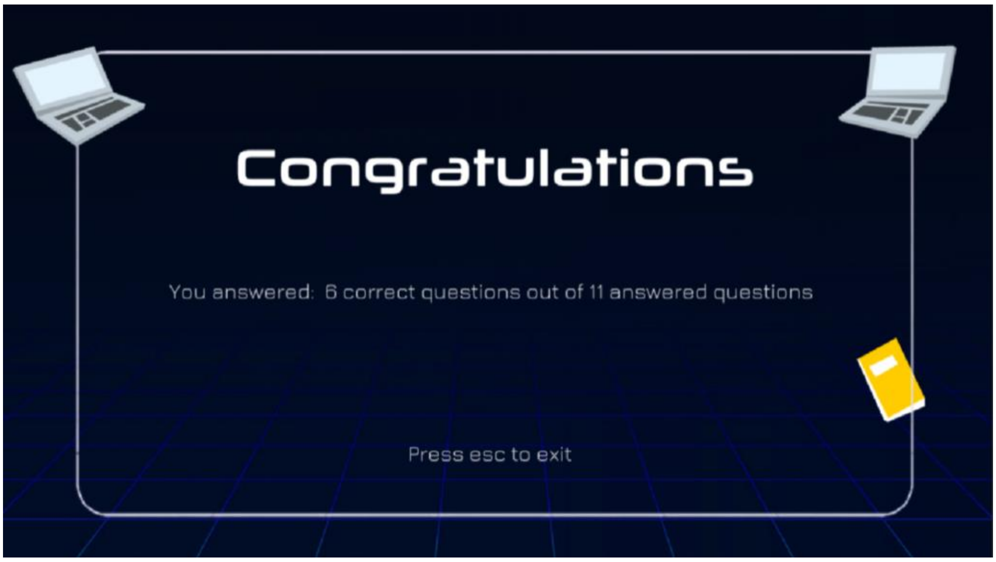

Figure 11 Successful completement screen

3.3 Indicators of the OCEAN model in the game

In the context of this thesis, the game measures only extraversion and openness to experience. Based on the findings of previous studies as reposted in the Sections 2.6 and 2.9, extraversion is assessed through the following indicators:

- Color preference for the avatar, choosing between red and blue as shown in Figure 12.
- Color preference during the game, selecting between red and blue.
- Use of music and sound effects during gameplay (Figure 13). The settings screen will be accessible via the setting button on the top left corner of the game (Figure 2).
- Agreement or preference for displaying the player's name on the final leaderboard (Figure 12).
- Desire for socializing, reflected in the selection of a chair in the game.

Figure 12 Initial screen of the game

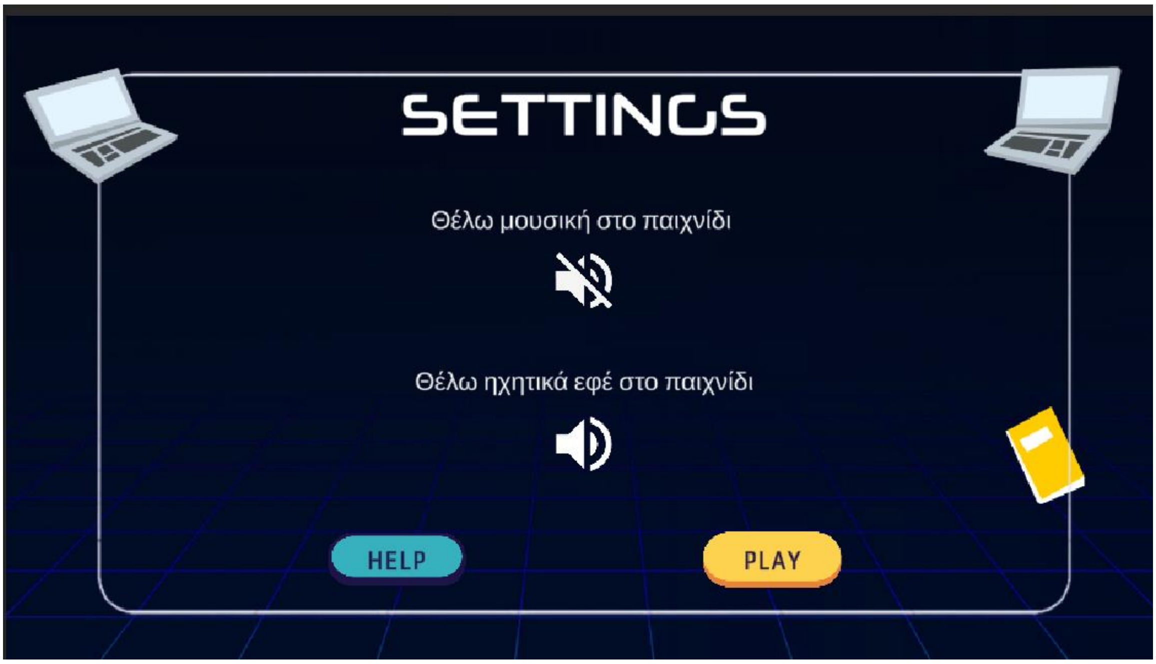

Figure 13 Settings screen

Openness to experience is evaluated using the following indicators:

- Curiosity demonstrated by visiting all the rooms in the game.
- Visiting the art room within the game.
- Selections made in the art room based on the paintings shown (Figure 9)
- Final score achieved in the quiz, indicating academic success.

These specific indicators were chosen to capture and measure extraversion and openness to experience within the game, ensuring the collection of valuable data for the classification algorithms. The data for each participant in the survey was collected and underwent pre-processing procedures to ensure the appropriate format for running the classification algorithms.

3.4 The Case Study

The following procedure was followed for conducting the experiment/case study among the students of the Databases course:

Initially, the professors of the Databases course informed the students about the case study and notified them of their eligibility to participate. To encourage participation, a 0.5 bonus motivation was offered to the students. However, the bonus was given only to those students who successfully passed the final exams.

To express their interest in participating in the study, the students were given a one-week timeframe. They were required to complete a participation form, using Google Forms, which ensured accessibility for all students. The form included fields for their university email address, full name, university registration number, and their experience in video games.

A total of 174 students indicated their interest in participating and then were subsequently enrolled in a dedicated sub-course on the university's LMS. Most of the students (78,7%) had previous experience in video games. This sub-course served as a platform for the students to express their concerns and ask questions about the survey procedure. The tutors responsible for the sub-course provided additional information and addressed any queries raised by the students.

One week later, the final procedure took place via zoom platform. Zoom was chosen as the call platform for its familiarity to both students and teachers. The Zoom call was scheduled on a day and time that did not conflict with other lessons. During the Zoom call, the students were instructed to download and install the game onto their personal computers. The game was compatible with Windows and Linux operating systems. Throughout the game installation and run, any questions or issues that arose regarding the installation process were addressed and resolved. After playing the game, two files were generated: one recording the students' behaviour and another containing their answers to the quiz questions. It was mandatory for the students to upload both files to the LMS. Upon completing the file uploading process, the students were required to fill out the BFI questionnaire (Annex B) in Google Forms. This questionnaire served as a confirmation of their agreement to take part in the study. Uploading the files and completing the questionnaire were necessary steps for the students to receive the extra bonus. The Zoom call was attended by a total of 149 students, who actively participated in the procedure.

During the gameplay, it is important to note that the students did not have the ability to pause the game. However, they were able to end the game by pressing the escape keyboard button (esc). Despite this instruction, it was observed that many students played the game more than once, even though the overall score they would achieve did not influence the extra bonus. Some students appeared determined to continue playing until they successfully completed the game, disregarding the instruction to play it only once. Furthermore, a significant number of students stopped the game at different times, possibly indicating a lack of thorough reading of the instructions or unfamiliarity with the quiz questions.

3.4.1 The sample

In order to collect user data and their corresponding BFI scores, we conducted the study with the students of the department of Applied Informatics of the University of Macedonia. A total of 149 students participated in the study, and the only requirement for participation was enrolment in the Databases course. Students from different academic levels were included in the study. Those who successfully completed the procedure described earlier, gained the additional bonus upon their success in the final exams.

3.4.2 The data preprocessing

The data collected from the students, which were uploaded to the LMS platform, underwent a necessary preprocessing procedure. The behavioural data were stored in a .txt file in CSV format to facilitate processing in Excel. A total of 149 files, each containing data for an individual student, were processed in the desired format. For every student a total of 21 variables were collected regarding their behaviour and choices in the game. Since the game was played more than one time, and sometimes were interrupted suddenly, the data couldn't be represented in binary format. For example, the color of the avatar could be recorded as "Blue" twice and "Red" three times. Table 1 depicts the variables used in the game, the opposite variable value, and the type of variable. For example, a player could choose whether "Blue Avatar" or "Red Avatar", that is the opposite variable value.

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” variable is Boolean, becoming true when the player has visited all the rooms within the game environment. The “Final score” variable is a decimal number indicating the score achieved in the last played game. The remaining variables mentioned above are numerical, representing the total count of occurrences for each variable within the different runs.

In addition to the behavioural data from the uploaded files, it was crucial to process the answers from the BFI questionnaire as well. The Big Five Inventory (BFI) scores for each student were computed by reversing the scores of the negative questions and then averaging the scores of the questions related to each personality trait. This methodology is described in section 4.1 of the study. This involved calculating scores for two specific traits: Extraversion and Openness to Experience. 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 resulting mean falls within a range of 1 to 5. In the Denden's et al, (2018) 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. 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”. This data pre-processing stage ensured that the collected data was organized and prepared for further analysis.

Both BFI scores and behavioural data included the student registration number, allowing us to merge the files into a single dataset. However, it is important to note that the student registration numbers were solely used for data matching purposes and were removed in the experiments for anonymity and privacy reasons. We used Python as our preferred language for running the classification algorithms. To handle and analyze the data effectively, we relied on the Pandas library. Pandas is a powerful open-source tool that allowed us to load the Excel file and easily process the data for running the algorithms.

3.5 BFI Questionnaire and scoring

The BFI questionnaire that was used in this study was employed as part of the research methodology (Papadimitriou, 2019). To minimize translation discrepancies, a bilingual researcher performed a back-translation procedure. This Greek version was utilized to ensure that every participant could fully comprehend each question.

Annex A displays the original version of the BFI questionnaire for the questions regarding Extraversion and Openness to Experience. Annex B displays the Greek version of the questionnaire as used in the study. It's worth noting that some questions in the BFI questionnaire have a negative scoring format, which means that the scoring needs to be reversed. In this case, the score of the participant should be subtracted from 6. This way, a score of 3 remains as 3, while a score of 5 becomes 1.

To calculate the BFI score for each specific personality trait, the scores of all the questions related to that trait are averaged.

3.6 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. Table 2 provides an overview of the specific scikit-learn functions employed for each algorithm.

Table 2 Classification algorithm and scikit learn function

Classification Algorithm	**Scikit learn function**
Naïve Bayes	sklearn.naive_bayes.GaussianNB
Decision Trees	sklearn.tree.DecisionTreeClassifier
k-NN	sklearn.neighbors.KNeighborsClassifier
Logistic Regression	sklearn.linear_model.LogisticRegression

The performance of each algorithm was evaluated by employing the evaluation metrics provided by the 'sklearn.metrics' module, namely Accuracy, Cohen's-Kappa, F1 score and AUC-ROC curve metrics.

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. Most 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.

The optimal results for predicting Extraversion across all four algorithms are presented in Table 3. Notably, k-NN outperformed the other algorithms in this context. Interestingly, despite k-NN's better overall performance, Logistic Regression also presents satisfying results with an accuracy of 0.70 and an F1 score of 0.76. However, it's essential to consider the AUC-ROC values in the context of model balance between precision and recall. In this context, k-NN achieves a more balanced AUC-ROC curve with a value of 0.74.

Table 3 Extraversion prediction Results

Classifier	Accuracy	Cohen's-Kappa	F1 score	AUC-ROC
Naïve Bayes	0.66	0.31	0.58	0.58
Decision Trees	0.63	0.27	0.65	0.64
k-NN	0.73	0.46	0.73	0.74
Logistic Regression	0.7	0.4	0.76	0.64

In Table 4, we present the optimal results for predicting 'Openness to Experience' using the four employed algorithms. Notably, Naïve Bayes emerges as the top performer for all the evaluation metrics. Specifically, it achieved the highest accuracy (0.73), a satisfactory Cohen's Kappa value (0.45), an F1 Score of 0.63, and an AUC-ROC score of 0.73. These findings underscore Naïve Bayes as the optimal choice for predicting 'Openness to Experience'.

Table 4 Openness to Experience prediction Results

Classifier	Accuracy	Cohen's-Kappa	F1 score	AUC-ROC
Naïve Bayes	0.73	0.45	0.63	0.73
Decision Trees	0.57	0.24	0.58	0.65
k-NN	0.57	0.18	0.63	0.62
Logistic Regression	0.63	0.29	0.63	0.57

The optimal algorithm, along with the respective results of all metrics, is detailed in Table 5. Our model in predicting the Extraversion, achieved an accuracy score of 0.73 and a Cohen's agreement of 0.46. 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. The values of AUC-ROC are high across both personality traits.

Table 5 The evaluation metrics of the classification algorithms for each personality trait

Personality Trait	Classifier	Accuracy	Cohen's-Kappa	F1 score	AUC-ROC
Extraversion	k-NN	0.73	0.46	0.73	0.74
Openness	Naive Bayes	0.73	0.45	0.64	0.76

4 Conclusion

4.1 Summary and conclusions

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 (Afroza et al., 2021; Denden et al., 2018). A similar study conducted by Denden et al, (2018) where they worked with forty four participants, including 34 learners who played the game and completed the BFI questionnaires. For extraversion they 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 Denden et al, (2018) study. Notably, our accuracy in Openness to Experience is slightly higher than that on Denden et al., (2018) (0.70) when using the Naïve Bayes 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 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. 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.

The facets of personality and psychological well-being bear great significance for the preservation of mental health. In my opinion, technology and games specifically, offers significant potential in modeling personality. Games and similar approaches can serve as early indicators for educators, parents, or psychologists, by giving them the opportunity to intervene when necessary, prior to circumstances escalating beyond manageable proportions. Given the increasing attachment of children with mobile and desktop games, where understanding their current psychological states can be complicating and challenging, further research is imperative to yield more valuable outcomes. Researchers have the potential to leverage existing gaming platforms and practices for further development and refinement in this area.

4.2 Research limits and limitations

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. However, this may have had a negative impact on the reliability and accuracy of the gathered data. 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.

Another limitation worth noting is that the research was conducted only once and within a single audience. To ensure the generalizability of the findings and validate the results, it is mandatory to replicate the case study with a larger and more diverse audience.

4.3 Future extensions

Future research contains the data analysis of the quiz answers, to identify patterns in the responses. 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.

Since personalized games can reduce the cognitive load and mental effort within a game and increase immersion, 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.

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Annex A – BFI questionnaire (Extraversion and Openness to Experience) in English

Below the BFI questionnaire questions regarding the Extraversion and Openness are presented with E and O letters in the beginning respectively. Where 1 is strongly disagree, 2 is somewhat disagree, 3 neither agree nor disagree, 4 somewhat agree and 5 is strongly agree.

I see Myself as Someone Who..

E-Is talkative
O-Is original, comes up with new ideas
E-Is reserved *
O-Is curious about many different things
E-Is full of energy
O-Is ingenious, a deep thinker
E-Generates a lot of enthusiasm
O-Has an active imagination
E-Tends to be quiet *
O-Is inventive
E-Has an assertive personality
O-Values artistic, aesthetic experiences
E-Is sometimes shy, inhibited *
O-Prefers work that is routine *
E-Is outgoing, sociable
O-Likes to reflect, play with ideas
O-Has few artistic interests *
O-Is sophisticated in art, music, or literature

Annex B – BFI questionnaire (Extraversion and Openness to Experience) in Greek

This is the Greek translated version exactly in the form given in the students.

E-Είμαι ομιλητικός/ή.

O-Είμαι πρωτότυπος/η, επινοώ νέες ιδέες.

E-Είμαι επιφυλακτικός/ή.

O-Είμαι περίεργος/η για πολλά διαφορετικά πράγματα.

E-Είμαι γεμάτος/η ενέργεια.

O-Είμαι πολυμήχανος/η, βαθυστόχαστος/η.

E-Δημιουργώ πολύ ενθουσιασμό.

O-Έχω ζωηρή φαντασία

E-Τείνω να είμαι ήσυχος/η (/πράος/α).

O-Είμαι εφευρετικός/ή.

E-Διαθέτω ισχυρή προσωπικότητα.

O-Εκτιμάω τις καλλιτεχνικές, καλαίσθητες εμπειρίες.

E-Είμαι μερικές φορές ντροπαλός/η (/συνεσταλμένος/η), διστακτικός/η.

O-Προτιμάω δουλειά που είναι ρουτίνα.

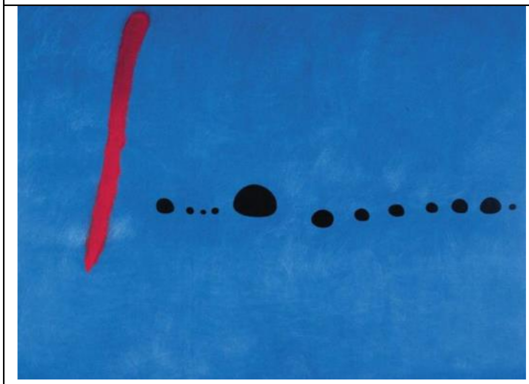
E-Είμαι εξωστρεφής, κοινωνικός/ή.

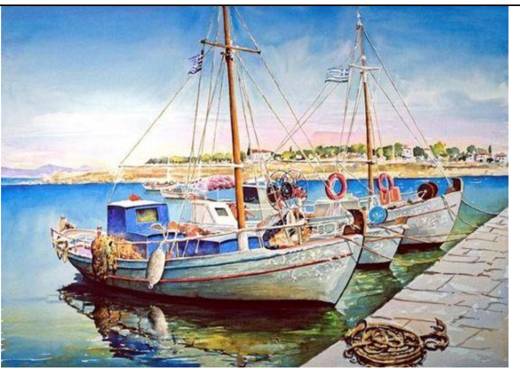
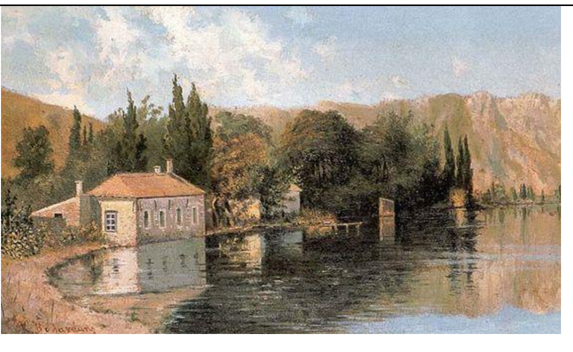
O-Μου αρέσει να αναλογίζομαι/συλλογίζομαι, να παίζω με ιδέες.

O-Έχω λίγα καλλιτεχνικά ενδιαφέροντα

O-Διαθέτω εκλεπτυσμένο γούστο στην τέχνη, τη μουσική ή τη λογοτεχνία.

Annex C – Table with paintings

Painting	Artist	Style
 Source: wassilykandinsky.net, Composition VII, 1913	Wassily Kandinsky	Abstract
 Source: joan-miro.net ,Blue II, 1961	Joan Miró	Abstract
 Source: wassilykandinsky.net, Composition VIII, 1923	Wassily Kandinsky	Abstract

 Source:unsplash.com , Untitled, Unknown Date		Abstract
 Source: thegreekartist.com, Spetse Boats, Unknown Date	Zografos Family	Classic
 Source:wikiart.org, Seashore of Poros, 1837-1907	Konstantinos Volanakis	Classic

 Source:nationalgallery.gr, First Steps, 1892	Iakovidis Georgios	Classic
 Source:nationalgallery.gr, Children's Concert, 1900	Iakovidis Georgios	Classic
 Source:www.bonhams.com, The Backwater, 1859-1923	Charles William Wyllie	Classic

 Source: artuk.org, The Old Mill, Boulogne, France, 1853-1923	Charles William Wyllie	Classic
 Source: thegreekartist.com, Naousa, Unknown Date	Zografos Family	Classic
 Source:jones-terwilliger-galleries.com, Sunny Malcesine Harbor, Unknown Date	Evgeny & Lydia Baranov	Classic

 Source:nationalgallery.gr, Ships At Anchor, ca 1886-1890	Konstantinos Volanakis	Classic
 Source:artrenewal.org, Two Young Girls with a Dog in an Interior, 1867	Theodore Gerard	Classic
 Source:mutualart.com, Les confitures de roses à Megara, 1852–1909	Theodoros Rallis	Classic
	Pop Maria	Classic

Source:nikias.gr, The 424 military hospital, Unknown Date		

Annex D – Conference Contribution Paper

The following paper has been accepted for presentation at the 22nd European Conference on e-Learning (ECEL 2023) and it will be included in the conference proceedings.

Chatziavgeri Aikaterina Satratzemi Maya, “Analysing Gaming Behaviour: Insights on Personality Traits”, 22nd European Conference on e-Learning (ECEL 2023), 26-27 October 2023, Pretoria, South Africa.