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Towards a system of customized video game mechanics based on player personality: Relating the Big Five personality traits with difficulty adaptation in a first-person shooter game ☆

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A B S T R A C T

While personality is known to moderate the kind of video games people like to play, the link between personality and game mechanics has not been explored. Finding such a link can enable customizing game mechanics based on personality, potentially making games more enjoyable and suited to a wide range of players. The present work investigated the relationship between the Big Five personality traits and four different implementations of difficulty adaptation, a popular game mechanic, in a first-person shooter game. In Study 1, a linear regression model was derived to relate the five personality traits with enjoyment (ENJ) and gameplay duration (DUR) in the four difficulty adaptations. In Study 2, this regression model was used to construct a predictor that chose a difficulty adaptation which maximized ENJ and DUR based on player personality. The predictor was tested against dynamic difficulty adjustment (DDA), which matched difficulty to user performance. ENJ and DUR were significantly higher in the prediction group than the DDA group. The present work highlights the importance of difficulty adaptation as a game mechanic, and suggests that personality could also be related to other game mechanics. Accordingly, a framework for personality-based game mechanics customization is proposed to foster future research.

1. Introduction

1.1. Personality and video games

Anyone who has ever owned a piece of modern computer technology, from the large (desktop PCs) to the small (smartphones) has probably played a video game at some point or another. The term *video game* itself today can refer to casual games like Candy Crush and Angry Birds, graphically realistic, immersive behemoths like Far Cry or Call of Duty, and anything in between. Despite their all-pervasive nature, it is apparent that not everyone likes playing video games in equal measure, and that different people like different genres of games. Research in the last decade has lent a measure of empirical insights into these intuitions, and it all relates to that one exemplification of an individual: *personality*. The concept of human personality has been grappled with by scientists and philosophers alike, who have tried to objectify and deconstruct it, as a way to formalize people's likes, dislikes, and ultimately who they are as individuals. Game researchers and psychologists have not been far behind in trying to find a link between video game play and personality, since playing video games is a voluntary activity that individuals do in their free time, which says a lot about their personality.

Numerous studies have found that personality affects both the kind of games that people like to play [1–7] and their play style [8,9]. Several studies have also found that matching a video game to player personality results in a more enjoyable playing experience [10,11], and, in the case of serious games, improved performance [12]. The links between game genre preference, play style, and personality, suggest that a game can also be individualized for a player based on their personality. Such individualization has the potential to make games more enjoyable and that players want to play for a long duration. Video game designers want their games to sell well, which means making games that can be enjoyed by a wide range of audience. Over the decades, distinct game genres,

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such as first-person shooters, role-playing games, platformers, simulation, and racing. have emerged. However, even within one genre, there is a high variability in the enjoyment experienced by players for a particular game, just as there is variability in how much different people like games in general [13]. Game designers could thus benefit from individualizing their games so that they appeal to as wide an audience as possible without compromising on core gameplay. While commercial game designers have the resources to make large, good-looking games that they can hope to sell despite the lack of any individualization, designers in other domains, like serious games and casual games, can benefit even more from individualization to make their games more enjoyable.

Using personality preferences to individualize the game experience has been suggested before [14–16], but has not yet been empirically tested for. One of the few commercial video games known to use personality-based adaptation is *Silent Hill: Shattered Memories* [17], in which non-playing characters ask the player some questions by which the player's personality profile is created and used to adapt gameplay elements. However, being a commercial game, the exact mechanism is not known. Realizing personality-based game individualization requires looking more closely into the aspects that make video games enjoyable.

While aspects like high fidelity graphics, deep gameplay, and multiplayer features are obvious ways to get people to enjoy games, they are one of the many techniques at the game designers' disposal. Anyone who has ever played Tetris for long knows that it's not any sort of graphics, but the game mechanic of dexterously and emphatically completing one row after the other, and the fact that the pieces fall faster and faster as one progresses, that makes Tetris addictive. Such a dynamic interaction is a particular example of a *game mechanic*, loosely defined as "the various actions, behaviours and control mechanisms afforded to the player within a game context" [18]. Examples of game mechanics include difficulty adaptation, level design, avatar customization, reward systems, etc. While there is plenty of research on personality and video games in general, the relationship between game mechanics and personality is relatively underexplored. Previous studies on gamified systems have found links between personality traits and game mechanics like rewards and leaderboards [19], while others propose a matrix of game mechanics and personality traits that could be related [20]. However, results of these studies cannot be generalized to video games; moreover, they miss some important mechanics like difficulty adaptation. Other studies looked at the effect of the similarity between player personality and game character on enjoyment [21]. Besides these few examples of studies that dealt with game mechanics, most of the other previous research has tended to treat video games as black boxes. Thus, there is limited empirical evidence on what kind of difficulty adaptation would a person with a particular personality enjoy, or what kind of in-game reward would spur them on, or what complexity of level design would they prefer, and so on. Understanding this link could help making video games much more enjoyable and individualized for a particular player.

1.2. Difficulty adaptation in video games

Among the many game mechanics elements that have an impact on how much players enjoy and how long they play a game, *difficulty adaptation*, which involves dynamically changing the game difficulty based on certain criteria, has become one of the most prominent ones. In general, difficulty adaptation comes in two types:

1.2.1. Dynamic difficulty adjustment

Dynamic difficulty adjustment (DDA) is the process of modulating the systems of a game world to respond to a particular player's abilities over the course of a game session [22]. The diversity in games makes this definition necessarily a broad one, since which systems of the game to modulate and how to measure or derive a player's abilities are highly game-dependent. Generally, DDA attempts to adjust game difficulty to match player skill, so that the player is neither bored (low difficulty, high skill) or overwhelmed (high difficulty, low skill), with such balancing theorized to increase enjoyment [23]. The range of actual DDA implementations, however, is quite diverse, from the simple, such as scaling task difficulty to match derived or computed user performance [24], to the more complex, such as player models to adapt game AI [25], adjusting opponent tactics in addition to player systems [26], weighted rules to select game AI actions [27], applying and updating game strategies immediately rather than perform iterative learning [28], and procedural level generation [29]. DDA implementation by scaling task difficulty parameters has been a popular game mechanic, especially in serious games [24,30,31] and casual games [32].

The first-person player game considered in the present work (described in detail in Section 2.1.1) consisted of the player being able to do a single type of action ("shoot"), and an enemy being able to do a single type of behaviour ("attack"). Games that contain a limited number of parameters benefit from using difficulty scaling to implement DDA, whereby the parameters are compared to preset threshold values and accordingly adjusted [33], and therefore DDA was implemented as difficulty scaling. Additionally, it was reasoned that DDA implemented as simple difficulty scaling would be a fairer comparison to the difficulty curves (described next), and could also increase the genericity and applicability of the results.

1.2.2. Static difficulty curves

Another approach used by game designers is to construct a difficulty curve, which specifies how the difficulty level of a game changes as a function of either time or distance travelled in the game (according to some game-specific metric) [34,35]. It is defined by the game designer and, unlike DDA, does not depend on player performance during the game; therefore, it is termed *static*. Static difficulty curves are especially useful in situations where assessing performance, as required by DDA, is either not possible or does not accurately reflect the game designer's intention for the player. Difficulty curves come in various flavours, and have been used in various commercial video games; prominent examples are high difficulty level in the beginning which decreases over time/distance (REVERSE), linearly increasing difficulty with plateau after a point (PLATEAU), and linearly increasing difficulty interspersed with rest periods of low difficulty (REST) (Fig. 1).

Game designers usually consider two kinds of difficulty: absolute [36], or nominal difficulty [37], which is the difficulty due only to the characteristics of the game, and perceived difficulty, which depends on the skill of the player and experience with the game [36]. Adams [36] provides the following concise equation to estimate perceived difficulty:

$$\text{Perceived difficulty} = \text{absolute difficulty} - (\text{power provided} + \text{in-game experience})$$

The assumption here is that the more power (weapons, ammo, shields, etc.) a player is provided, and the more experience they have with the game, the less difficult they will perceive the challenges of the game to be. However, it must be observed that the "equation" above is merely a simplified rule-of-thumb, and that "in-game experience" might include previous experience with similar games, dexterity with controls, etc. Inclusion of these subjective factors renders determining perceived difficulty an

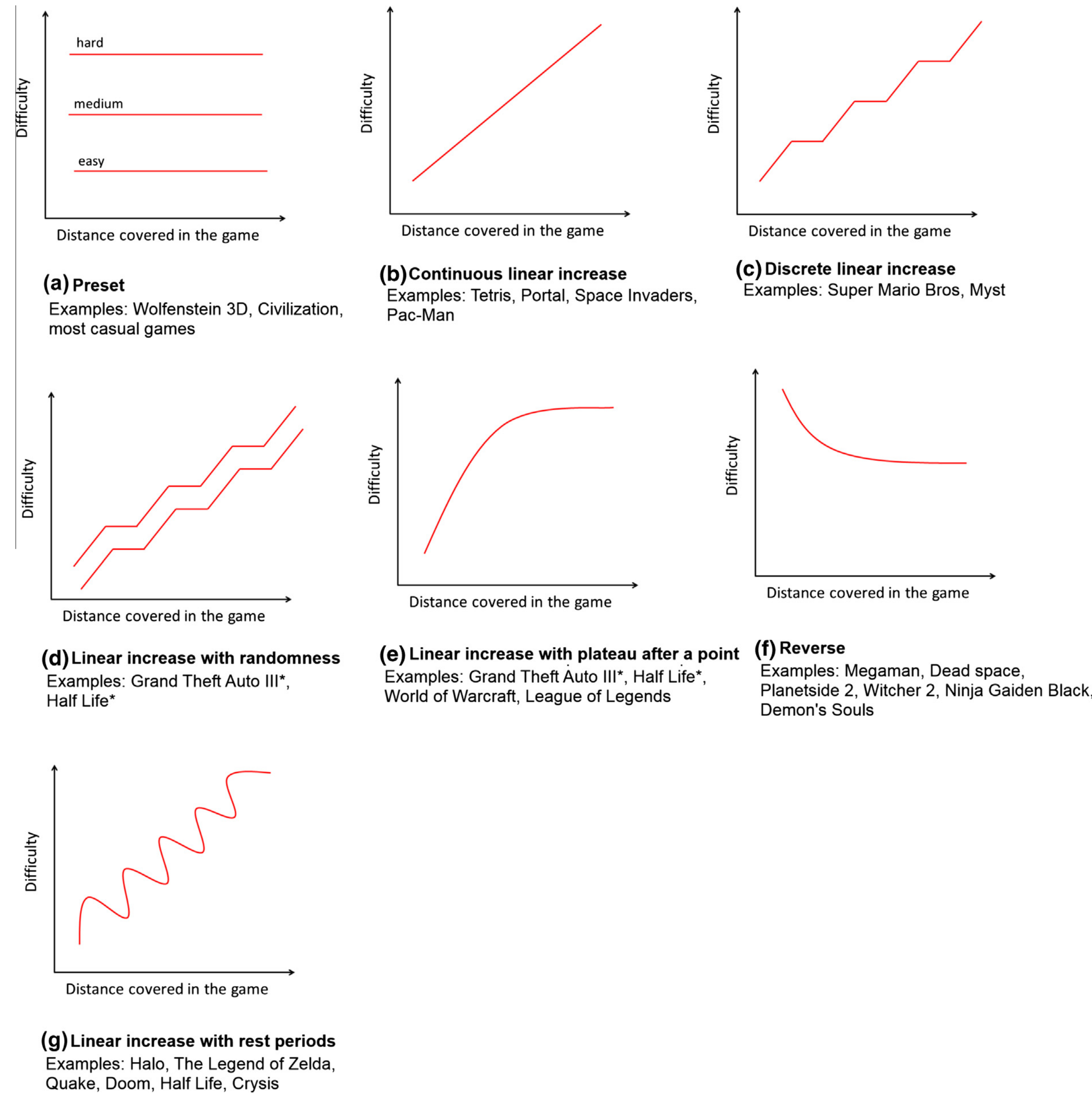

Fig. 1. Examples of static difficulty curves, partially adapted from [92], with examples of video games employing that curve. Games marked with an asterisk * have more than one difficulty curve.

approximation, and would likely confound comparison among the different difficulty curves. Therefore, absolute, or nominal difficulty was considered in the present work.

1.3. Aims and hypotheses

The first aim of the present work was to investigate if there is a relationship between personality and player enjoyment and duration of gameplay in four difficulty adaptation conditions: DDA, PLATEAU, REVERSE, and REST (Study 1). Based on a relationship, a better player response, i.e., higher enjoyment and duration of gameplay, should be achievable if personality information were used to select one of the four difficulty adaptation conditions. Using personality information to select one among several implementations of difficulty adaptation is similar to the suggestion by van Lankveld [38], who proposed using personality profile to select a game scenario. Therefore, the second aim of the present work was to use the identified relationship to predict a difficulty adaptation condition that maximizes both enjoyment and duration of gameplay for a player based on their personality (Study 2). Personality was assessed using the Big Five personality factors [39], which has been used in a number of studies about video games [40,41]. The reduced Ten-Item Personality Inventory (TIPI) was used for efficiency, since answering long questionnaires can produce fatigue and boredom because of the repeated and similar nature of the questions [42]. For example, the Big-Five Inventory [39] has been validated in several studies and is psychometrically superior to TIPI, but contains 44 questions, which was considered too many for online, anonymous players to answer. Online users are known to have a limited attention span [43], sooner moving to another tab than answer long questionnaires, and so TIPI was weighed to be a good balance between reliability and brevity. Admittedly, TIPI is unable to discern differences between the individual facets within the Big-Five dimensions [44,45], but the design of the present study did not require data at this granularity.

Previous research on personality and motivation has revealed several links between the Big Five personality traits and various motivations to play games, which were used to derive some hypotheses for Study 1 (Fig. 2). People with what is known as an *autotelic personality* do things for their own sake, rather than to achieve some external goal [46,47]. Such individuals are internally driven, and tend to prefer a balance of seeking challenge and building skills [48,49]. An autotelic personality, in turn, is related to openness to experiences [50]. Since DDA ensures a balance of challenge and skill, openness to experiences was hypothesized to be related to enjoyment in DDA (**Hypothesis 1**). PLATEAU was the easiest difficulty adaptation condition, with difficulty linearly increasing and plateauing at the midpoint. Participants were therefore expected to progress well in this condition, and experience high levels of competence. People with high conscientiousness find progress in games to be more motivating than other game elements [51], and therefore conscientiousness was hypothesized to be related to enjoyment in PLATEAU (**Hypothesis 2a**). Agreeableness is related to feelings of competence in playing video games [2], and therefore agreeableness was also hypothesized to be related to enjoyment in PLATEAU (**Hypothesis 2b**). Extraversion is related to an adventure motivation to play online games, that included items like enjoying new challenges and wanting to play well on difficult games [41]. In general, extraversion has been linked to preference for difficult tasks [52] and high levels of challenge [53]. Therefore, extraversion was hypothesized to be related to enjoyment in REVERSE, since REVERSE started with the highest difficulty and was expected to be the hardest condition (**Hypothesis 3**).

Previous work has found a positive link between conscientiousness and time spent playing video games [4]. Additionally, previous research suggests that people with high levels of conscientiousness are less prone to boredom [54,55], and so might perform an activity thoroughly and for a longer duration. Therefore, conscientiousness was hypothesized to be related to duration of gameplay in all difficulty adaptation conditions (**Hypothesis 4**).

For Study 2, the following research question was postulated:

[Study 2] Q1. If there is a significant relationship between the Big Five personality traits and enjoyment and duration of gameplay, does assigning a difficulty adaptation condition to a player based on this relationship result in a higher enjoyment and duration of gameplay, as compared to assigning them a predetermined difficulty adaptation condition?

2. Study 1: Investigating and quantifying the relationship between Big Five personality traits and enjoyment and duration of gameplay in four difficulty adaptation conditions

2.1. Material and methods

2.1.1. The game

A custom-made first person shooter game was used in the present study, augmented with the four difficulty adaptation conditions: DDA, PLATEAU, REVERSE, and REST. Although the game was based on common first-person shooter principles like player point-of-view and enemies to shoot, it was created from scratch

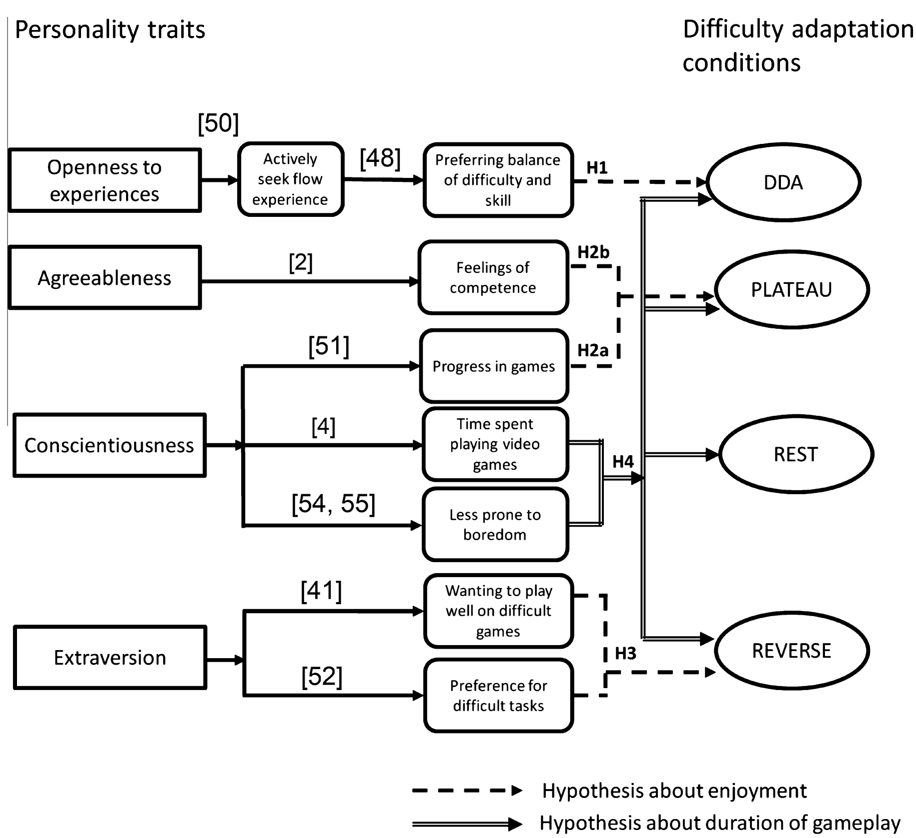

Fig. 2. Factors that are affected by the Big Five personality traits (solid lines leading to boxes), which in turn might moderate player enjoyment (dashed lines) and duration of gameplay (double lines) in the four difficulty adaptation conditions. Emotional stability was not hypothesized to affect enjoyment or duration of gameplay.

specifically for this study. Depending on the group to which a participant was randomly assigned, one of the four conditions was activated. The game was put online on a university server and participants were invited to play the game by posting on game forums, sending an email on university mailing lists, etc. In total, 160 anonymous participants took part in the study. The game forums used to advertise the study were predominantly about topics related to first-person shooters; the email on the university mailing lists also clearly mentioned the game to be a first-person shooter. Therefore, while gaming preferences or gaming history of the anonymous participants was not asked, there is reason to believe that the participants were indeed more inclined to prefer first-person shooters than other game genres.

Upon going to the game website, participants were first informed about the study, and asked to click on a button if they agreed to participate. Subsequently they were prompted to fill in their age and gender (both optional) and the 10-item reduced Big Five personality traits questionnaire [44]. The 10-item Big Five personality questionnaire consists of 10 questions, answers to which are combined to derive values for the following five personality traits: openness to experiences (O), conscientiousness (C), extraversion (E), agreeableness (A), and emotional stability (ES).

The game was set in a post-apocalyptic landscape (Fig. 3), in which the participant controlled a player with a gun containing infinite ammo. The landscape was filled with 300 zombies of various types moving towards the player. The aim was to kill all the zombies. The game would end either when all zombies were killed or if any zombie got too close to the player, in which case the player would "die". The number of zombies left, and the number of zombies killed per minute ("kill rate") were displayed on the top right. An aspect of the zombie killing storyline that could potentially play a role was the possible violent nature of the game. A preference for violent video games has been linked to low agreeableness and low emotional stability [1]; the question, however, is whether the present zombie-killing first-person shooter should be considered a violent video game or not. Anderson [56] define violent video games as those that depict intentional attempts by individuals to inflict harm on others, and count games like Wolfenstein 3D [57] in the violent category. Should zombies in the present game be considered "others" in Anderson's definition? In fact, as the author of the preceding study admits in another work [58], the definition of what constitutes a violent video game is not universally agreed upon. We would argue that violent video games are characterized more by gory violence [58], gratuitous killing [59], realistic scenarios [60], and humanoid characters [61]. The zombie killing objective of the present game was not gratuitous, not graphically realistic (upon shooting, the zombies disappeared amidst a 3 s splattering animation), and the player could not kill the zombies in any special, extra-violent way. The zombie-killing mechanic, in fact, was as linear as Mario stepping on mushrooms in Super Mario Bros [62]. It can be reasoned, therefore, that the game of the present study does not fit into the classical violent games category, and violence-preferring personality traits correlations would not emerge. Another aspect of the storyline that could play a role was its fixed nature, since a lack of exploratory gameplay can reduce enjoyment in games [63]. However, this effect is usually seen in role-playing games with large sceneries to explore. The presence of a fixed story in the present game was therefore not expected to affect enjoyment.

2.1.2. Difficulty adaptation conditions

Difficulty was dependent on the following elements:

- Speed of zombies: how fast the zombies moved.
- Detection radius of zombies: if the distance between a zombie and the player was less than or equal to this radius, the zombie would begin moving towards the player.

Difficulty was increased by increasing the speed of zombies by 1, and increasing the detection radius by 100; it was decreased by decreasing the two elements by the same amounts. These two parameters were considered to be the only reasonable difficulty parameters to change, since the game contained no other objective except the zombie-killing one. The threshold values against which

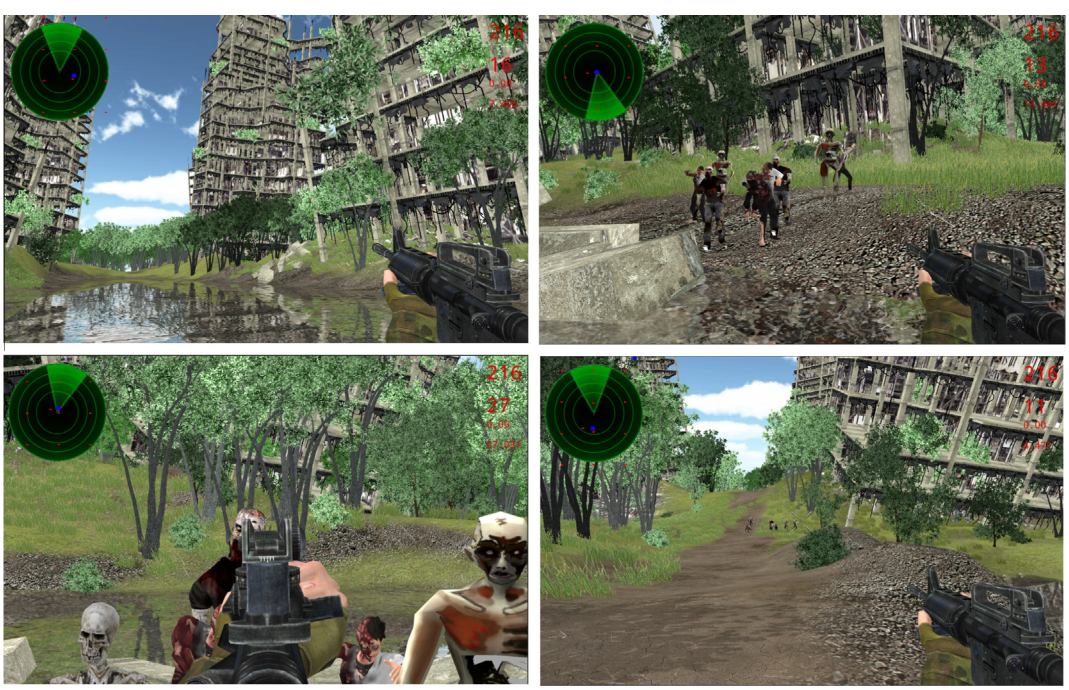

Fig. 3. Screenshots of the first person shooter zombie killing game. The game consisted of a player placed in a post-apocalyptic landscape, with the aim of killing all the zombies.

to compare the parameters were derived after several rounds of internal testing. The initial difficulty in all conditions was: speed of zombies = 1, detection radius = 100. The difficulty adaptations were time-based, with difficulty being changed at intervals of 30 s. The four adaptations worked as follows:

Difficulty adaptation	Implementation
DDA	Difficulty was increased if the kill rate was above 10 kills/min; it was decreased if it was below 5; otherwise it was kept unchanged.
PLATEAU	Difficulty was linearly increased and plateaued at *MaxDifficulty*/2 after 300 s. The linear increase was based on a maximum gameplay time of 600 s and maximum difficulty of *MaxDifficulty*. *MaxDifficulty* was the maximum possible viable difficulty level for the game, set using pilot tests, and 600 s was the average expected duration of gameplay.
REVERSE	Difficulty was initialized at *MaxDifficulty*, and then linearly decreased with time, plateauing at *MaxDifficulty*/2 after 300 s. The linear decrease was based on the same linear curve as PLATEAU.
REST	Difficulty was alternatingly increased and decreased at 30 s intervals. At the intervals of 30 s, 90 s, 150 s, ..., difficulty was linearly increased based on the same linear curve as PLATEAU. At the intervals of 60 s, 120 s, 180 s, etc., difficulty was set to 50% of the level at the previous interval. Thus, there were intervals of increasing difficulty interspersed with intervals of low difficulty.

2.1.3. Outcome measures

(1) Enjoyment (henceforward referred to as ENJ): This was a self-reported measure, derived from the following post-game question: "How much did you enjoy this game?". Participants had to answer on a scale of 0 to 100. 0 represented "not enjoyed at all", and 100 represented "enjoyed a lot".
(2) Duration of gameplay (henceforward referred to as DUR): This was recorded as the total duration of playing the game.
(3) Performance: To ensure fair comparison across the difficulty adaptation conditions, it was necessary that performance be independent of absolute difficulty level. Otherwise, DDA and REST, which increased difficulty without a bound, would produce a higher performance number. Therefore, performance was not computed as an absolute number, but rather as a percentage of the maximum possible performance at any given point. Towards that end, a maximal performance was defined as a kill rate of 20 kills/min. To ensure that performance does not drop for lack of zombies in the vicinity, the performance computation was triggered only when a zombie entered a "kill radius" of 50 game units, and was paused when there were no zombies within the kill radius. The kill rate was computed in windows of 60 s, with kill rates in every window being cumulatively added as a percentage of the maximal kill rate of 20 kills/min. The final performance number was derived by dividing the cumulative added percentages by the number of intervals (Eq. (1)). The kill radius and the maximal kill rate were derived from extensive pilot tests.

$$\text{Performance} = 100 * \frac{1}{M}\sum_{i=1}^{M}\frac{\text{kill rate in current window of 60 s [kills/min]}}{20} \quad (1)$$

Here, M = number of 60 s windows

Additionally, participants' willingness to play the game again was gauged by asking the post-game question "Would you play this game again?", to be answered as a choice between "no", "maybe", and "yes".

2.1.4. Data analysis

A one-way analysis of variances (ANOVA) was used to test for differences in the three outcome measures between the four difficulty adaptation conditions. ENJ and DUR were modelled as a linear combination of the Big Five personality traits to investigate if there is a relationship between the two outcome measures and the five personality traits. Performance, which is a measure that depends highly on individual skill with the game genre and previous experience with video games in general, was expected to be different across the four difficulty adaptation conditions. More skilled players were expected to perform better, while some conditions, like PLATEAU, were inherently easier than others like REVERSE, and were expected to elicit higher performance. So even though performance was measured, it was not included in the model to relate with the Big Five personality traits.

Hierarchical multiple linear regression analysis was used to develop a model for predicting ENJ and DUR from the five personality traits values in each difficulty adaptation condition. In the first step of the regression, all five traits were used as predictors in the model. In case any trait(s) were non-significant ($P > 0.05$), they were discarded in the next step of regression, and the change in explained variance was checked. The model was accepted if the change in explained variance from the step containing all traits to the step containing only significant traits was less than 5%. Regression through the origin [64] was used, since an ENJ or DUR value in the absence of any personality traits did not make sense. Additionally, the aim was to compare the outcomes of the regression equations among the four adaptation conditions, and not to use the values in any absolute sense. IBM SPSS Statistics version 22 was used to perform the statistical analyses.

2.2. Results

The investigated population showed the following personality traits: openness to experiences (Mean = 4.92, SD = 1.32), conscientiousness (Mean = 4.7, SD = 1.31), extraversion (Mean = 4.69, SD = 1.27), agreeableness (Mean = 4.67, SD = 1.28), emotional stability (Mean = 4.61, SD = 1.37).

2.2.1. ENJ, DUR, and performance in the four difficulty adaptation conditions

A one-way ANOVA did not reveal significant differences in ENJ across the four difficulty adaptation conditions. DUR, on the other hand, was significantly higher in PLATEAU than in DDA and REST, while performance was significantly higher in PLATEAU than all other difficulty adaptation conditions (Fig. 4).

2.2.2. Age and gender

28 participants either did not report age or reported frivolous values (1000, 500, etc.). The remaining 132 participants were between 17 and 45 years old, with a mean of 30.6 years, and standard deviation of 8.4 years. 37 participants did not report gender; of the remaining 123, 79 reported being male, and 44 female. Age exhibited no significant correlations with any of the outcome measures in any of the difficulty adaptation conditions, as determined by Pearson product-moment correlation. Dividing the

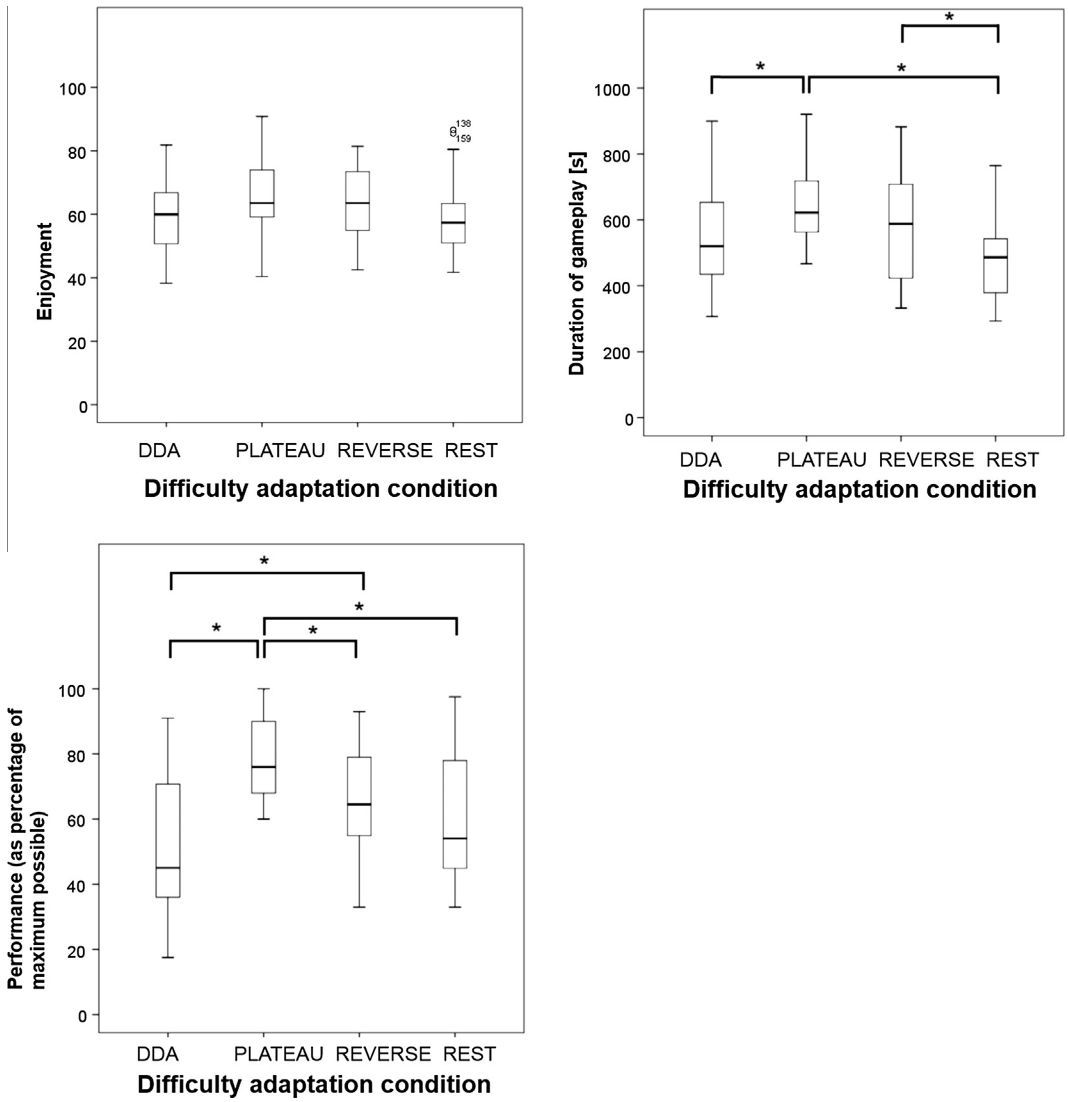

Fig. 4. Box plots of ENJ (top left), DUR (top right) and performance (bottom left) in the four difficulty adaptation conditions. Differences marked with an asterisk * are significant at the $P < 0.05$ level. $N = 40$ participants in each difficulty adaptation condition.

population sample by gender produced no significant differences in any of the outcome measures.

2.2.3. Relationship between personality traits and ENJ, DUR

In the hierarchical multiple regression analysis, a different pair of personality traits was found to significantly predict ENJ and DUR in each of the four difficulty adaptation conditions ($P < 0.05$; Table 1). The relationship between personality traits and ENJ is more evident in the scatterplots between the pair of traits which significantly predict ENJ in each difficulty adaptation condition and ENJ in that condition (Fig. 5). A similar relationship was observed for DUR (Fig. 6).

2.2.4. Relationship between ENJ, DUR, and performance

Pearson product-moment correlations were run to determine the relationships between ENJ, DUR, and performance in the four difficulty adaptation conditions. ENJ and DUR were positively correlated in PLATEAU and REVERSE (Fig. 7). In DDA and REST, ENJ and DUR had different correlations, based on the answers to the question of willingness to play again. Specifically, ENJ and DUR were positively correlated in DDA among participants who answered "yes" to the question of willingness to play again, and negatively correlated in DDA and REST among participants who answered "maybe" and "no" respectively (Fig. 7). While performance was not correlated with ENJ in any of the difficulty adaptation conditions, it exhibited significant positive correlation with DUR in DDA ($r = .523$, $P = .001$) and REST ($r = .766$, $P < .001$).

2.3. Discussion

Performance exhibited significant differences between the difficulty adaptation conditions (Fig. 4), which was expected. It was significantly highest in PLATEAU, which was again as expected, since PLATEAU was an inherently easy difficulty adaptation condition. Performance also exhibited a significant positive correlation with DUR in DDA and REST. Since DDA increased difficulty in response to increased performance, the fact that participants who played longer also performed well is not surprising. In this regard, REST, with its unbounded linear-like difficulty increase, functioned similar to DDA.

ENJ was significantly predicted by openness to experiences and conscientiousness in DDA, thus confirming **Hypothesis 1**. ENJ was significantly predicted by conscientiousness and agreeableness in PLATEAU, thus confirming **Hypotheses 2a** and **2b**. ENJ was

Table 1
Unstandardized regression coefficients for hierarchical multiple linear regression through the origin to predict ENJ and DUR from the five personality traits. Missing trait values indicates non-significance ($P > 0.05$). Change in R^2 from the model including all five traits to the model including two traits for each difficulty adaptation condition smaller than 5% in each case. $N = 40$ participants in each difficulty adaptation condition.

Personality trait	DDA		PLATEAU		REVERSE		REST	
	ENJ	DUR	ENJ	DUR	ENJ	DUR	ENJ	DUR
Openness	7.057						7.423	
Conscientiousness	5.074	73.6	8.060	73.4				104.2
Extraversion		41.9			6.567	66.6	5.060	
Agreeableness			6.013	37.07				
Emotional Stability					6.208	38.01		

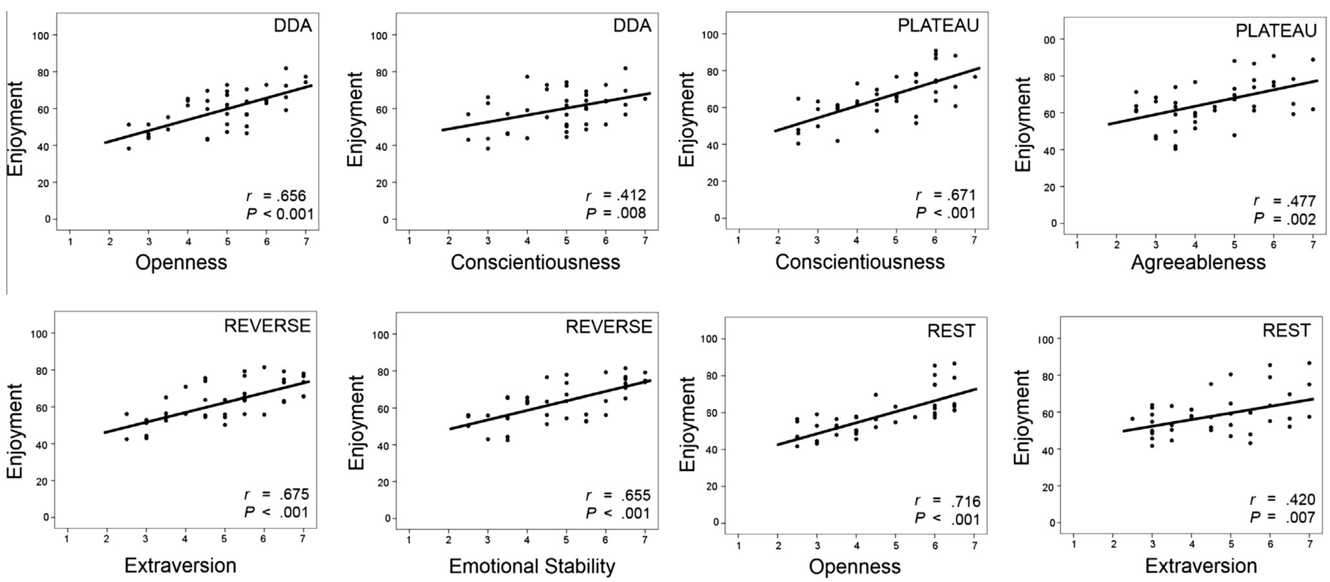

Fig. 5. Scatterplots of personality traits and ENJ in the four difficulty adaptation conditions; only those traits which significantly predict ENJ are shown.

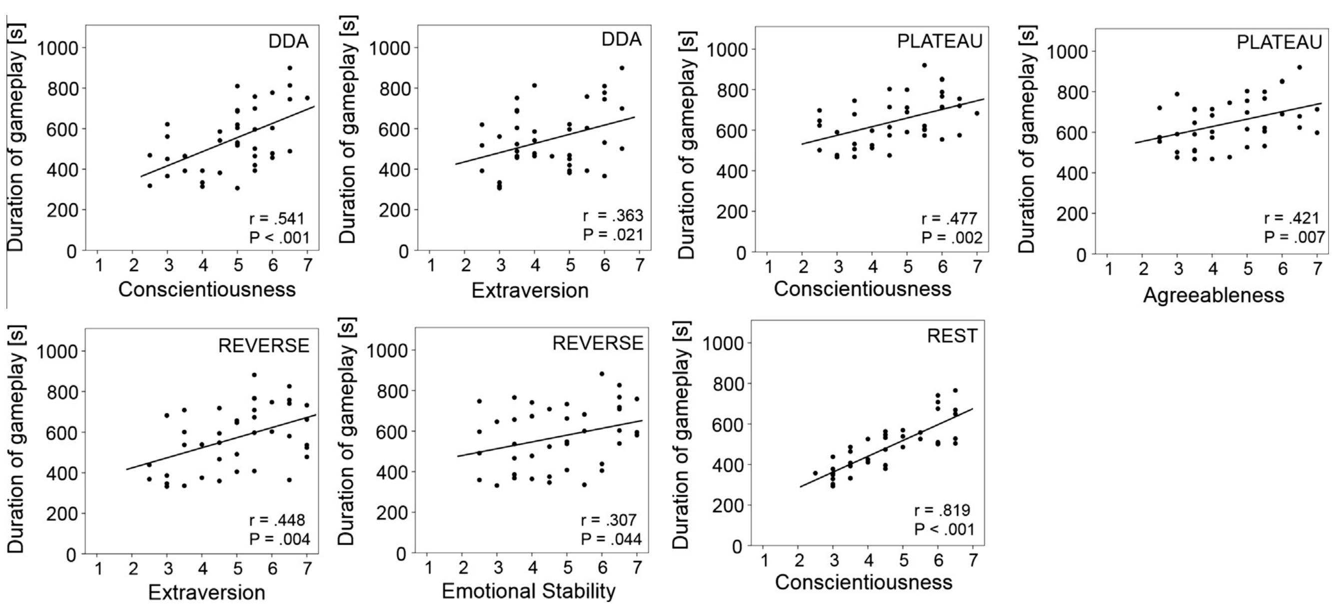

Fig. 6. Scatterplots of personality traits and DUR in the four difficulty adaptation conditions; only those traits which significantly predict DUR are shown.

predicted by extraversion in REVERSE, thus fulfilling **Hypothesis 3**. In REVERSE, ENJ was also significantly predicted by emotional stability, which was surprising. A tentative explanation could be the positive link between emotional stability and preference for shooting games [2], with participants high on emotional stability inherently enjoying the first-person shooter game more in a high

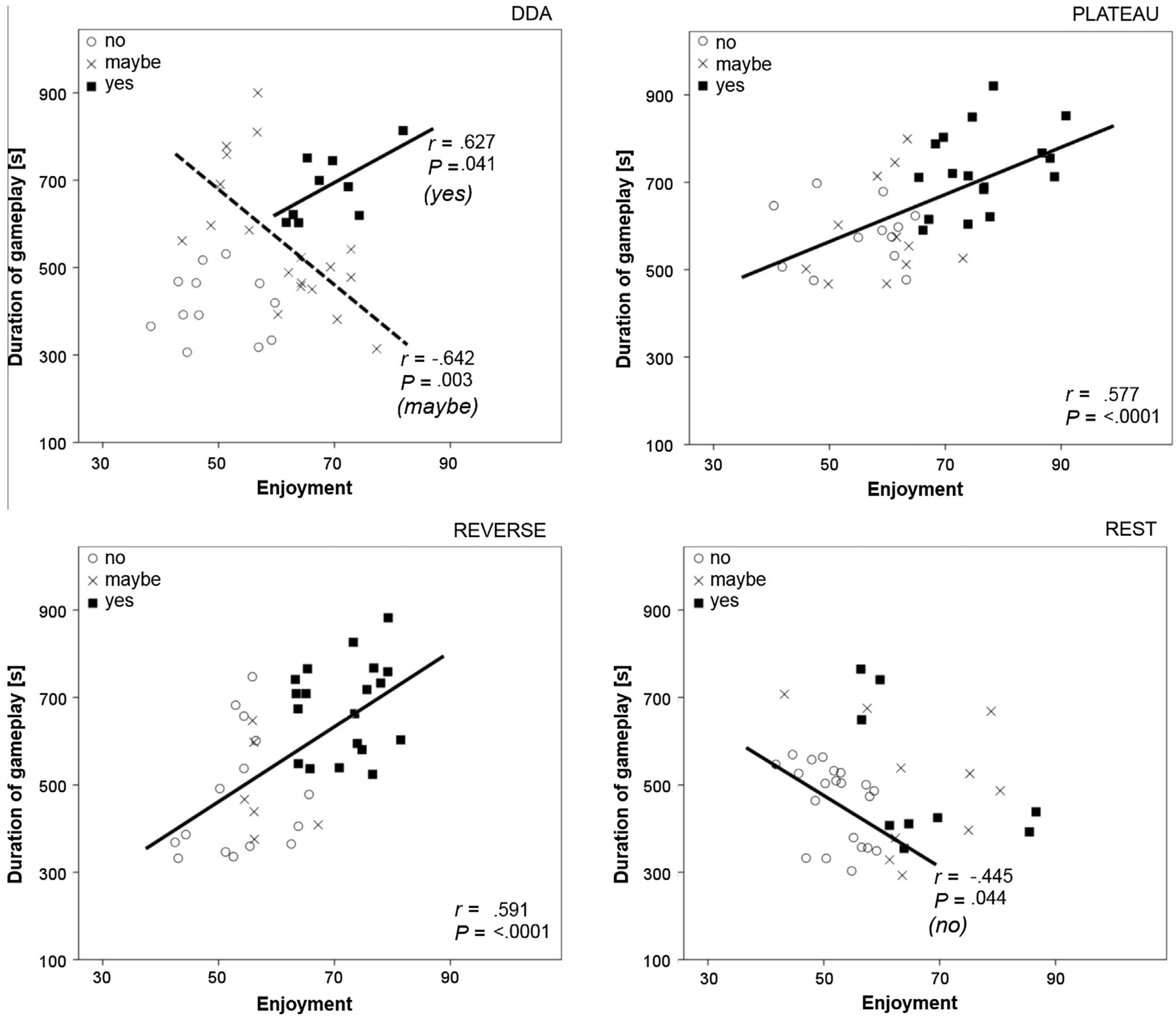

Fig. 7. Scatterplots for ENJ and DUR in the four difficulty adaptation conditions, with the data points categorized according to the answer to the post-game question of willingness to play again. $N = 40$ participants in each difficulty adaptation condition.

difficulty level entailed by REVERSE. Conscientiousness was a significant predictor of DUR in all difficulty adaptation conditions except REVERSE, thus partially confirming **Hypothesis 4**.

The scatterplots between the pair of traits that significantly predicted ENJ in each difficulty adaptation condition and ENJ in that condition (Fig. 5) revealed an even spread of the traits, which never went below 2.5 (out of a maximum of 7), indicating that none of the participants self-reported such a low extreme of personality. One reason for this might be the unwillingness of participants to honestly self-report personality, even in an anonymous study. Nevertheless, the even spread of the values increases confidence in the regression coefficients being used as predictors.

ENJ and DUR were highly positively correlated in PLEATEAU and REVERSE (Fig. 7), which also explains why these two were the only adaptation conditions in which both ENJ and DUR were predicted by the same pair of personality traits (Table 1). In DDA, ENJ was highly correlated to DUR only for the subset of participants who answered "yes" to the question of willingness to play again. For participants who answered "maybe" in DDA and "no" in REST, ENJ was negatively correlated to DUR (Fig. 7). A possible explanation for this in DDA could be that with steadily increasing difficulty, participants either got really good at the game, quit early and reported having enjoyed a lot, or they plodded on for a longer duration, were disappointed with the high difficulty at these latter stages, and reported low ENJ. In both cases, they were unsure if they want to play the game again, and answered "maybe". The same explanation could apply to REST, though a bit stronger, since in this case participants who played longer but enjoyed less, or those who played for a short duration but enjoyed more, answered "no" to playing the game again. Intuitively, ENJ and DUR should be positively correlated: one would expect that a player would play a game for a long duration only if they are highly enjoying it, and vice versa. Indeed, time spent in doing a task (such as playing games) has been used as a measure of intrinsic motivation in many studies [65–67]. The ENJ-DUR mismatch that occurred in DDA for some players goes against game developers' intention that players should play the game for a long duration, and that they should play the game repeatedly. Therefore, we believe that DDA should be looked into more closely, since it is the most popular difficulty adaptation technique, but seems unable to simultaneously produce high ENJ and DUR in some cases. One possible reason for DDA's failure to do so could be its stringency about always increasing difficulty in response to increasing performance. Results of the present study suggest that games employing difficulty adaptation could benefit from not relying solely on DDA, but perhaps combining it with other difficulty curves, e.g. PLATEAU.

In conclusion, Study 1 found a quantifiable relationship between personality traits and ENJ and DUR in the four difficulty adaptation conditions, in the form of regression coefficients. In the subsequent Study 2, this relationship was used to construct and test a predictor that assigned a difficulty adaptation condition which would maximize ENJ and DUR for a player based on their Big Five personality traits. Since ENJ and DUR were not always correlated, the predictor in Study 2 considered the regression models of both ENJ and DUR in assigning a difficulty adaptation condition.

3. Study 2: Using the relationship between personality traits and ENJ, DUR to select the best difficulty adaptation for a player

3.1. Material and methods

3.1.1. The prediction strategy

In Study 1, a quantifiable relationship in the form of regression coefficients was derived to relate the Big Five personality traits and ENJ and DUR in the four difficulty adaptation conditions (Table 1). The regression coefficients were used to derive the difficulty adaptation condition that maximized ENJ and DUR. In case ENJ and DUR were maximized by different difficulty adaptation conditions, one was randomly chosen (Algorithm 1).

Algorithm 1. Personality-based difficulty adaptation selection

Inputs: Big Five personality traits, coded as P_1, P_2, P_3, P_4, P_5
Enjoyment regression coefficients ENJ_{mn}
Duration of gameplay regression coefficients DUR_{mn}
Output: Difficulty adaptation condition that maximizes both ENJ and DUR, or one of the two
for each difficulty adaptation condition k **do**
  $ENJ_k = \sum_{i=1}^{5} ENJ_{ki} * P_i$
  $DUR_k = \sum_{i=1}^{5} DUR_{ki} * P_i$
end for
$ENJ_{MAX} = (k \mid ENJ_k = \max(ENJ_1, \ldots, ENJ_4))$
$DUR_{MAX} = (k \mid DUR_k = \max(DUR_1, \ldots, DUR_4))$
if ENJ_{MAX} **equals** DUR_{MAX} **or** RandomNumberBetween(0, 1) > 0.5 **then**
  return ENJ_{MAX}
else
  return DUR_{MAX}
endif

The experimental protocol in Study 2 was the same as in Study 1, with the same first person shooter game, 10-item personality questionnaire, and outcome measures of ENJ, DUR. To test the effectiveness of the prediction strategy as a whole, it was compared against DDA, which is the most widely used difficulty adaptation technique [22,68–70]. Participants were randomly assigned to one of two groups: DDA-GROUP, which used DDA as the difficulty adaptation condition, or PREDICTION, which selected a difficulty adaptation condition based on the personality trait values (Algorithm 1). The PREDICTION group was formed of three sub-groups, based on the way the prediction algorithm chose the adaptation: PREDICTION-MATCH (ENJ_{MAX} equal to DUR_{MAX}), PREDICTION-ENJ (ENJ_{MAX}), and PREDICTION-DUR (DUR_{MAX}). Of course, the difficulty adaptation condition selected in any of the PREDICTION sub-groups could also be DDA.

3.1.2. Data analysis

Differences in ENJ and DUR were analysed with a one-way analysis of variances with three levels of factors: main group (DDA-GROUP vs. PREDICTION), prediction strategy within PREDICTION (PREDICTION-MATCH, PREDICTION-ENJ, and PREDICTION-DUR), and the assigned difficulty adaptation condition within PREDICTION (DDA, PLATEAU, REVERSE, REST). For the latter two analyses, the Sidak test was used for post hoc comparisons. The threshold for significance was set at $P = 0.05$.

3.2. Results

Eighty subjects participated in Study 2, out of which half were randomly assigned to DDA-GROUP and half to the PREDICTION group. In the latter, a majority of participants had a difficulty adaptation assigned as a result of a match between ENJ_{MAX} and DUR_{MAX} ($N = 22$); of the remaining 18, half were randomly assigned to ENJ_{MAX} and DUR_{MAX} each. In each sub-group, the difficulty adaptation condition chosen most often was PLATEAU (Table 2).

3.2.1. Differences in ENJ and DUR between DDA-GROUP and PREDICTION

There was a statistically significant difference in ENJ ($F(1,78) = 174.4$, $P < 0.001$) and DUR ($F(1,78) = 31.5$, $P < 0.001$) between PREDICTION and DDA-GROUP (Fig. 8, top). Within the PREDICTION group, there was a statistically significant difference in ENJ ($F(2,37) = 4.7$, $P = 0.015$) and DUR ($F(2,37) = 4.2$, $P = 0.022$) between the different prediction strategies. The Sidak post hoc test revealed that PREDICTION-MATCH exhibited significantly higher ENJ (mean difference = 7.49, $P = 0.014$) than PREDICTION-DUR and significantly higher DUR (mean difference = 96.1, $P = 0.018$) than PREDICTION-ENJ (Fig. 8, middle). Within the PREDICTION group, there were no significant differences in ENJ or DUR between the four assigned difficulty adaptation conditions (Fig. 8, bottom).

3.3. Discussion

A predictor that chose a difficulty adaptation condition based on player personality was able to elicit significantly higher ENJ and DUR as compared to a strategy of assigning DDA irrespective of personality. Of the 40 participants in PREDICTION, 22 were assigned a difficulty adaptation condition based on a match between maximizing ENJ and DUR. The efficacy of the prediction strategy was highlighted by the fact that it produced significantly better ENJ and DUR in spite of slightly less than half the participants being assigned a condition as a consequence of a random choice between maximizing ENJ and DUR. An alternative to the random choice was to use the willingness to play again answers from Study 1 to construct four multi-class supervised classifiers with the five personality traits as inputs, and three outputs: yes, no, and maybe. A mismatch between ENJ and DUR could then be resolved by choosing the adaptation condition whose classifier outputs a "yes" for the personality traits. This strategy was initially tried, but failed to cross-validate existing data. While it is difficult to speculate if a supervised classification strategy would be superior or inferior to the strategy of random assignment, results of the present study demonstrate the adequacy of our chosen approach.

In the PREDICTION group, 18 participants out of 40 were assigned PLATEAU, either as a result of a match between maximizing ENJ and DUR ($N = 12$) or one of the two ($N = 3$ each) (Table 2). PLATEAU being chosen the most often was not surprising, given that it was significantly predicted by conscientiousness and agreeableness (Table 1), which were high among participants of Study 2 (Table 2). Additionally, the specific values of the regression coefficients for PLATEAU were also quite high (Table 1). However, there were no significant differences between PLATEAU and the other difficulty adaptation conditions for ENJ or DUR. Thus, choosing PLATEAU as the default difficulty adaptation condition, instead of DDA, would not work in principle.

The next most frequently assigned difficulty adaptation was REVERSE ($N = 10$), owing to the combination of high values of

Table 2
Descriptive statistics of personality traits values of participants in the PREDICTION group of Study 2, organized according to the sub-group (MATCH, ENJ, DUR) and assigned difficulty adaptation condition.

		N	Openness		Conscientiousness		Extraversion		Agreeableness		Emotional Stability	
			M	SD	*M*	SD	*M*	SD	*M*	SD	*M*	SD
DDA-GROUP		40	5.22	1.35	4.48	1.15	4.5	1.21	4.72	1.34	4.51	1.31
PREDICTION		40	5.02	1.32	4.56	1.25	4.38	1.16	4.75	1.34	4.48	1.26
MATCH (*N* = 22)	DDA	4	6.13	.85	5.5	.70	4.62	.47	3.25	.64	4.87	1.71
	PLATEAU	12	5.17	.93	5.08	1.1	3.5	.63	5.95	.89	4.04	1.17
	REVERSE	6	3.92	1.2	3.33	.6	5.66	.93	4.83	.81	5.08	.91
	REST	0	-	-	-	-	-	-	-	-	-	-
ENJ (*N* = 9)	DDA	2	5.75	1.0	4.75	1.0	4	1.41	3.75	1.76	3.25	.35
	PLATEAU	3	5.17	2.3	6.33	.28	4.33	.28	4.83	2.25	4.33	1.52
	REVERSE	2	4	0	5	.7	4.50	.7	3	0	5.75	.35
	REST	2	6	0	3.75	1.06	5	1.41	4.25	1.06	3.75	1.76
DUR (*N* = 9)	DDA	3	4.67	1.0	5	.50	5.16	1.04	4	.86	4.66	1.25
	PLATEAU	3	6.17	.76	3.16	.76	3	0.0	4.5	.86	4.5	1.32
	REVERSE	2	5	.70	2.5	0	4	1.41	5.5	1.41	4	.7
	REST	1	7	0	7	0	3	0	5	0	5.5	0

extraversion and emotional stability, even though separately, the values of these two traits were not high in the whole sample (Table 2). Thus, the prediction algorithm was able to interpret the high values of a pair of personality traits in a way that led to REVERSE being assigned to some players. REVERSE is a choice of difficulty adaptation that seems unappealing at the outset, and one that not everyone would like. But for players with a personality predicted to prefer it, REVERSE was almost as enjoyable and resulted in almost as much DUR as the other conditions, with no significant differences (Fig. 8, bottom).

Participants were assigned DDA in two cases: either as being part of DDA-GROUP, or as a result of the prediction. The latter resulted in higher ENJ and DUR (Fig. 8, bottom), which highlights the fact that it is not DDA *per se*, but DDA assigned as an a priori, default choice, that resulted in low ENJ and DUR.

REST was not a popular choice, finding not a single match between maximizing ENJ and DUR (Table 2). One reason for this could be the quirk in the regression equation for DUR in REST, with only one personality trait, conscientiousness, being the significant predictor (Table 1). However, the significant predictors for ENJ in REST were openness and extraversion, two traits which are related to high levels of gaming [71,72]. Participants who were assigned REST had high values of openness and extraversion, and consequently experienced high ENJ and DUR for REST (Fig. 8, bottom). We could speculate that the regression coefficients of ENJ were truer predictors for the general preference for REST than the regression coefficients of DUR. This, together with the comparable values of ENJ and DUR in PREDICTION-ENJ and PREDICTION-DUR (Fig. 8, middle), supports the case for maximizing ENJ when maximizing both ENJ and DUR is not possible.

In summary, assigning a difficulty adaptation condition based on the found relationship between the Big Five personality traits and ENJ, DUR did result in higher values of ENJ and DUR, as compared to assigning them a predetermined difficulty adaptation condition, thus answering **Q1**.

4. General discussion and conclusions

The presented studies bring into focus the differences in player response in terms of ENJ and DUR that can result from different implementations of difficulty adaptation. It seems that not only is personality related to video game play as a whole, as was already demonstrated by numerous previous studies, but also to difficulty adaptation, which is a small, but clearly important, component of the mechanics of a video game. ENJ and DUR in each of the four adaptation conditions were sufficiently distinct to be predicted by a different pair of personality traits. The three static difficulty curves of PLATEAU, REVERSE, and REST seem to be viable alternatives to DDA in designing the difficulty adaptation game mechanic. Additionally, the lack of consistent correlation of ENJ and DUR observed for DDA in Study 1 indicates that combining DDA with a static difficulty curve could be beneficial, and merits further investigation. In using the personality traits as predictors of a regression model, the important result is not the absolute values of the regression coefficients, which may vary according to the sample chosen for constructing the model and the game genre, but the fact that if players with high values of certain traits are assigned a certain difficulty adaptation, they enjoy more and play for a longer duration. Game designers can use this knowledge to individualize gameplay for players based on their personality. The results of the present study, therefore, could be used to design more meaningful adaptive systems in games, potentially augmenting the existing areas of player-centered game design [73,74] and player modelling [25,75]. The present results could also foster

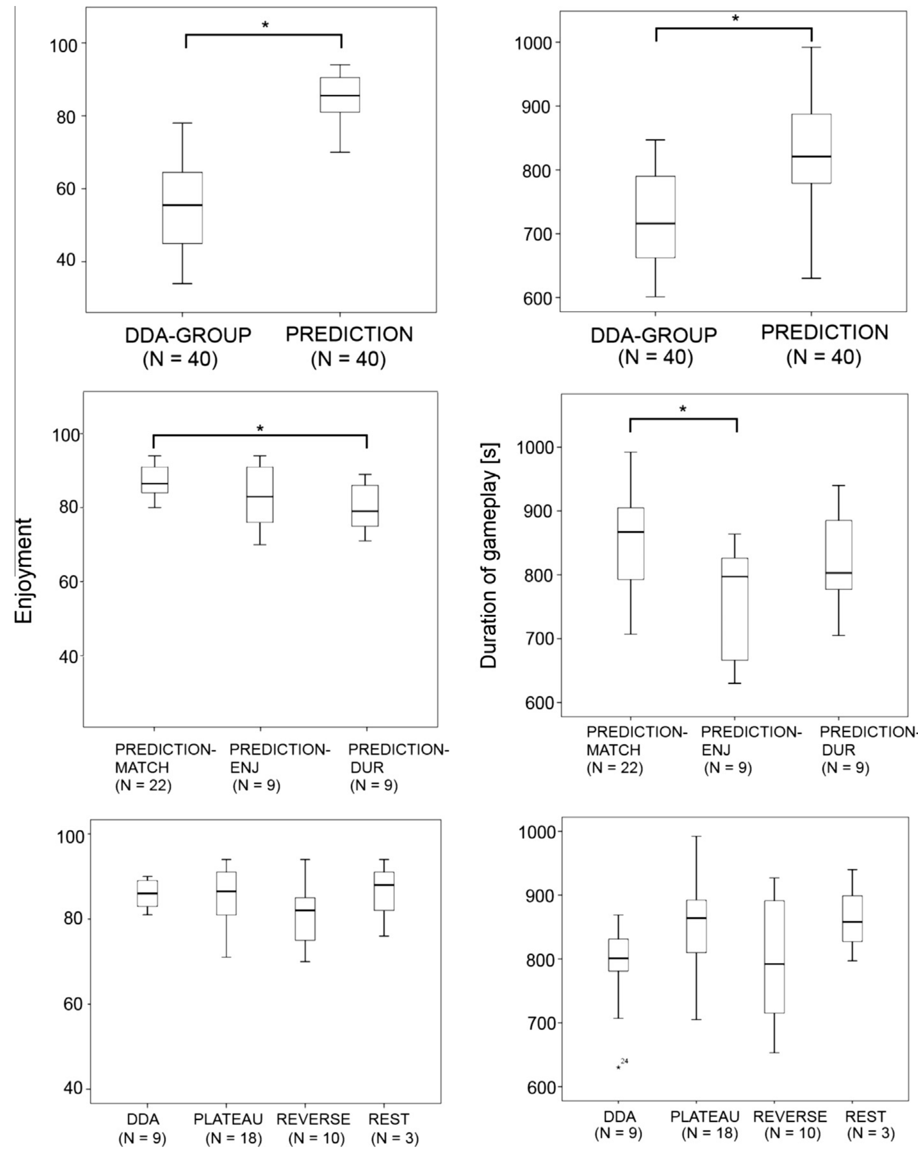

Fig. 8. Box plots of ENJ (left) and DUR (right), organized according to main groups (DDA-GROUP vs. PREDICTION, top), sub-groups within PREDICTION (PREDICTION-MATCH, PREDICTION-ENJ, PREDICTION-DUR, middle), and difficulty adaptation conditions within PREDICTION (bottom). Differences marked with an asterisk * are significant at the $P < 0.05$ level.

research into the use of personality as a technique of video game personalization, since personality has been under-utilized for that purpose [76].

The presented studies have a few limitations. Firstly, the anonymous, online, nature of the studies means that the personality traits values are not wholly reliable, or representative of the general population sample. Furthermore, the use of TIPI reduces the psychometric reliability of the derived personality traits. However, the clear trend of a pair of personality traits predicting player enjoyment and gameplay duration in distinct difficulty adaptation conditions does seem to point to a generalizable pattern, whereby certain personality traits are linked to certain kinds of game mechanics. While the particular mechanic considered in the presented studies was difficulty adaptation, the links to personality might also hold for other game mechanics, such as level design, or reward systems. Still, given the limited scope of TIPI, future research might benefit from using larger personality questionnaires, such as the Big-Five Inventory [39].

Secondly, adjusting difficulty parameters by comparing them against preset threshold values admittedly runs up against issues of parameter tuning [35], and the superiority of the predictor in Study 2 could be attributed to ill-chosen DDA parameters. While a more sophisticated DDA could have been implemented, for example by changing behaviour of the zombies [26], implementing comparable static difficulty curves would have been highly challenging. Implementing DDA as difficulty parameter scaling, using threshold values derived from extensive pilot tests, was reasoned to be a simpler but still reliable comparison to the static curves. Additionally, an important aspect of DDA, implemented by difficulty scaling or other sophisticated methods, is timing: *when* to change difficulty, i.e., the *pace* of difficulty change, is a strong determinant of player enjoyment [77,78]. That DDA and the difficulty curves used the same difficulty-change timestep is therefore a more equitable reason to rely on the fairness of comparing the two types of adaptations. Nevertheless, an avenue for future research could be a similar study with difficulty adaptation

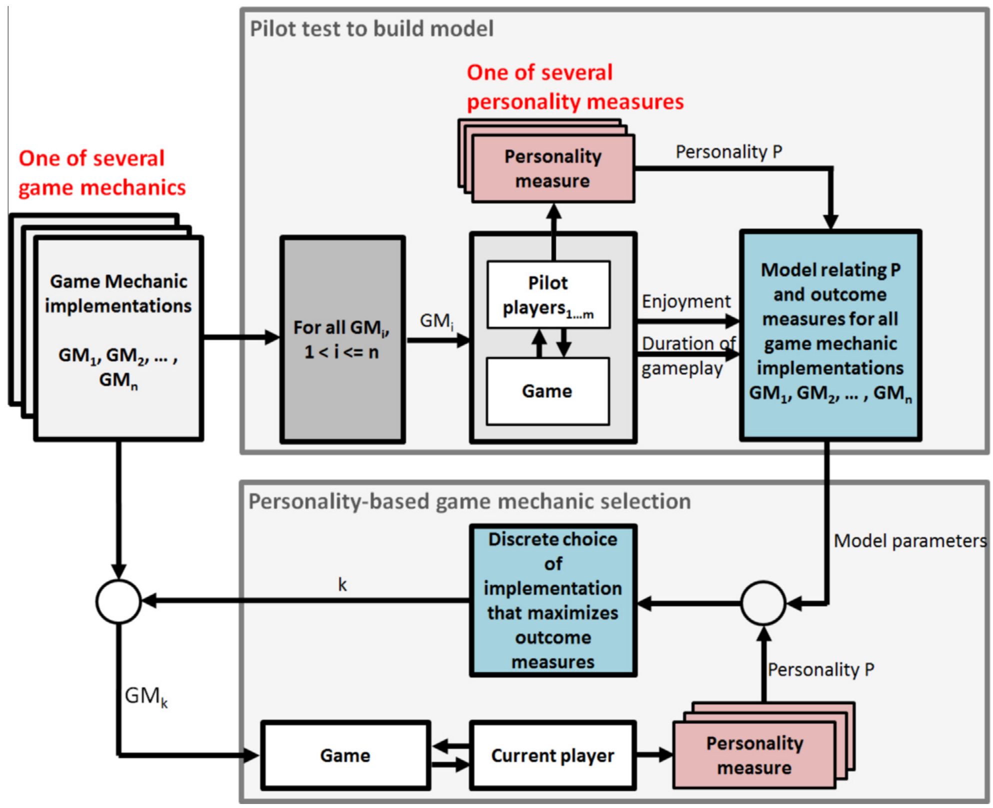

Fig. 9. Framework to construct a model relating personality and game mechanics, which can then be used to select a game mechanic implementation that optimally enhances game play.

implemented by more sophisticated methods, such as dynamic parameter tuning [79], player modelling [70], or adapting enemy behaviour [26].

Thirdly, the results might not be transferable to a different game genre, other than first-person shooters. While personality is theorized to influence the genre of games that people like to play [5], results on links between the Big-Five personality traits and preference for a game genre are mixed. Extraversion has been linked to preference for role-playing games and action games [1,80], and also to dancing games [3] and puzzle games [81]. Conscientiousness has been positively associated with preference for sport, racing, simulation games [80], and negatively to first-person shooter games [3]. Openness has been linked to platformer games [80]; it has also been found to be both positively [1] and negatively [81] related to games high on action content. Alternatively, it has been suggested that people with different personalities might not actually prefer different game genres, but experience the same genre differently [53]. While the preceding results demonstrate the highly subjective nature of personality and game preference research, with a relatively weak theoretical framework [82], it is apparent that links between personality traits and game genre preference, however tenuous, do exist. Additionally, most of the preceding works were correlational, survey-based studies; it can be argued that deriving gameplay experience and preferences by actually testing people playing real games in clearly differentiated genres might be more useful. Several studies have also looked at the link between personality and motivations to play games. Extraversion has been linked to relationship, adventure and achievement motivation [41], agreeableness to escapism and achievement motivation [41] and also to competence motivation [2], while openness has been related to a motivation for autonomy [2]. Different genres of games fulfil different motivations [83], and therefore differently implemented mechanics in one genre might be related to different personality traits. Hence, while the specific regression model that was derived in the present work might not hold for other game genres, or even other kinds of first-person shooter games, it seems reasonable to suppose that a link could be found between personality and game mechanics in other game genres as well. For example, users who like to play massively multiplayer role-playing games (MMORPGs) look to fulfil motivations such as achievement, relationship, escapism [84], which in turn are related to extraversion and agreeableness [41]; thus, a link might exist between these two traits and game mechanics in MMORPGs.

Personality is a widely studied concept with many general measures of personality besides the Big Five factors, e.g. Myer-Briggs personality test [85], the Personality Assessment Inventory [86], Personal Attribute Questionnaire [87], etc. Additionally, game researchers have developed several player types based on their personality, such as Bartle gamer types [88], Fullerton's player Types [89], and Weber and Shaw's player types [90]. One possible framework to use personality as an individualizing tool is to select an appropriate personality measure, a game mechanic that could produce individual differences, and then to construct a model that explains player behaviour for different implementations of the game mechanic in terms of the chosen personality measure (Fig. 9). Such a framework could be extended to include several game mechanics, eventually towards a system where game mechanics are customized based on player personality. It could also be applied to gamification, which consists of using game design elements in non-game contexts [91]. Personality-based individualization of gamified systems has been suggested [20] and tested [19] before, but lacks a systematic framework. The present work aims to be a first step towards a system of incorporating personality with game mechanics, in order to increase player enjoyment, the time that players invest in in playing a game, and to generally enhance the gameplay experience.

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