Play Style: Showing Your Age

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***Abstract*—Age has been shown to influence our preferences, choices, and cognitive performance. We expect this influence to be visible in the play style of an individual. Player models would then benefit from incorporating age, allowing developers to offer an increasingly personalized game experience to the player. To investigate the relationship between age and play style, we set out to determine how much of the variance in a player's age can be explained by his play style. For this purpose, we used the data from a survey ('PsyOps') among 13,376 'Battlefield 3' players. Starting out with 60 play style variables, we found that 45.7% of the variance in age can be explained by 46 play style variables. Furthermore, similar percentages of variance in age are explained when the sample is divided along gaming platform: 31 play style variables explain 43.1% on PC; 30 play style variables explain 53.9% on Xbox 360; 28 play style variables explain 51.7% on Playstation 3. Our findings have a high external validity due to the large and heterogeneous nature of the sample. The strength of the relationship between age and play style is considered 'large' according to Cohen's classification. Previous research indicates that the nature of the relationship between age and play style is likely to be based on life-time developments in cognitive performance, motivation, and personality. All in all, our findings merit a recommendation to incorporate age in future player models.**

I. Introduction

Player modeling is an emerging field of AI. However, the term *player modeling* lacks a clear definition, resulting in different authors providing different definitions [17]. We adhere to a general definition that player modeling is a field of AI that focuses on understanding and modeling the characteristics of a player. In our work, understanding and modeling primarily takes place through analyzing a gamer's play style (we define 'play style' as an individual's in-game behavior as measured by game play variables.) The result is a model that predicts certain properties of the player, such as skill or emotional engagement. The data in the model can potentially be used to adapt the game in order to offer the player a personalized game experience. The value of a personalized game experience grows as the gamer demographic diversifies. Most notably, video games have become increasingly popular among a wide range of age groups. The Entertainment Software Association reports that the average age of the American gamer is 30, and that 68% of gamers are 18 years or older.[1] Aging is accompanied by a host of physiological and psychological changes, such as a decline of cognitive performance, a shift to a more conscientious personality, and a decrease in achievement-based gaming motivations (See Section II.)

To our knowledge, age has not been incorporated into player models so far. To discover whether age influences relevant constructs in player modeling, we set out to answer the question: *How much of the variance in age can be explained by play style?* We conjecture that physiological and psychological developments from aging are expressed in play style. Consequently, we believe that play style is a strong predictor of age. If our conjecture is correct then player models would become more accurate if they control for age.

[1]March, 2012: http://www.theesa.com

II. Related Work

The link between age and play style has remained unexplored so far. However, there are at least three research areas that form a "bridge" between age and play style: cognitive performance, motivation, and personality. Though all three areas are intertwined, each merits separate consideration as previous research shows how each uniquely relates to both age and play style. The authors know of no other research areas that share this dual relationship. In particular, the following subsections will focus on the three bridging constructs: cognitive performance (Section II-A), motivation (Section II-B), and personality (Section II-C).

A. Cognitive Performance

Cognitive performance is defined as the capacity and efficiency of cognitive processes such as attention, memory, and perception.

Age & Cognitive Performance - It is well documented that cognitive performance deteriorates with age. We provide three examples of cognitive decline and how they relate to gaming. First, age is negatively correlated with performance on various components of spatial tasks [2], such as spatial pattern completion [15], and spatial memory [13]. Spatial skills are relevant for efficient navigation of a game world. Secondly, age is negatively correlated with learning and memory in general [7]. Both learning and memory are crucial in mastering game mechanics and completing tasks in video games. Thirdly, age is negatively correlated with performance on attentional tasks [1]. Many games are based on speed of action and dealing with high input and output rates. Attentional resources mediate the speed and quantity of the tasks that a player can perform at a given time.

Play Style & Cognitive Performance - As far as we were able to discover, the link between play style and cognitive performance has been exclusively examined from one perspective: how improvements in game performance lead to improvements in cognitive performance. Game performance is one aspect of play style consisting of the set of variables that describe

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the player's effectiveness at fulfilling the goal(s) of the game. Green & Bavelier [11] reported multiple cognitive performance improvements due to video game training. Among others, they found improvements in spatial cognition and attention. Chandramallika et al. [3] specifically explored the cognitive effect of video game training on older adults. They found that improvements in game performance were accompanied by improvements in various cognitive functions, including memory.

B. Motivation

Motivation is defined in our work as the *"forces acting either on or within a person to initiate behaviour."*[2]

Age & Motivation - Age correlates with gaming motivation. Yee [22] found that gaming motivations cluster into three categories: Achievement, Social, and Immersion. All three motivations decrease significantly with age. Achievement motivation decreases the most with an effect size around -0.3. Yee's research was conducted with a large sample (3000+) of MMORPG players.

Play Style & Motivation - We know of no research into the relationship between play style and motivation. Yee's findings (above) do contain indirect measures of play style. He asked participants to report on their play style and what factors of game play they valued. However, self-report measures are inherently unreliable [9]. Play style (as we define it) can be directly measured by tracking an individual's in-game behavior in terms of game play variables. Therefore, Yee's research into gaming motivation hints at a possible relationship between play style and motivation, but does not prove its existence.

C. Personality

Personality is discussed here in terms of the Big Five personality inventory [5]. The Big Five defines personality along the following dimensions: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

Age & Personality - Large cross-cultural samples have shown that age and personality correlate significantly. McCrae et al. [14] and Donnellan & Lucas [6] explored a total of over 40,000 participants over 6 countries. They found that Extraversion and Openness decrease with age, while Agreeableness and Conscientiousness increase (limited to late middle age, see [6]). Neuroticism decreased with age in all samples but one. The deviant sample showed a small positive trend for over 20,000 German participants. The size of the deviant sample renders the overall Neuroticism trend ambigious.

Play Style & Personality - Play style correlates significantly with personality [23], [16]. Lankveld et al. [20], [21] found correlations between play style and Extraversion within small samples. We continued the exploration of the link between play style and personality [19]. Our focus was on attaining a large sample size to increase the statistical power and external validity (defined as the validity of generalized inferences) of the findings by Lankveld et al. We confirmed the relationship between play style and personality with a large cross-cultural sample [19]. The results show three major themes: (1) Conscientiousness is negatively correlated with speed of action (subset of game play variables that define play style). (2) Variation in play style correlates most often and most strongly with personality, especially with Conscientiousness and Extraversion. (3) Work ethic (facet of Conscientiousness) correlates negatively with game performance (subset of game play variables that define play style). Furthermore, one additional finding was observed: Age correlates strongly with both play style and personality. This finding formed the starting point of our current research.

[2]Encyclopedia Britannica: http://www.britannica.com

III. Experimental Setup

The bridging constructs discussed in the previous section give us reason to expect a link between age and play style. Our experiment was aimed at finding out how much of the variance in age can be explained by play style. Variance is the average error between the mean and the collected data. The experimental setup consisted of a data collection (Section III-A) and a data analysis (Section III-B) phase. The experimental design is outlined below. It was initially setup to explore the link between play style and personality [19]. Though personality data was not used in our current investigation, the need to obtain personality data did shape the data collection process.

To answer the current research question, two requirements had to be met: (1) Play style should be meaningfully quantified in order to reflect underlying play style constructs (e.g., speed of action); (2) Sufficient participants should be recruited to attain high statistical power and external validity. The two requirements are discussed below. Next, the considerations and process behind attaining the personality data is briefly reviewed. This will supply the reader with additional insight into the experimental design. The review will remain brief as personality data was already brought into relation with age and play style in our previous work [19].

Requirement (1) was met by selecting a game that offered a publicly accessible game statistics database: the online first-person shooter Battlefield 3. The data was meaningfully descriptive as it detailed play style in terms of interesting choices ranging from player specializations to player performance on various metrics (see Section III-A for more details).

Requirement (2) was met by *marketing* the research toward the participant pool in such a manner as to create an almost viral enthusiasm to contribute. Our research project was dubbed 'PsyOps', and data collection was performed through a dedicated website. Here, participants could find promotional material such as game-related art work, as well as a promotional trailer explaining the basics of the research initiative. We reached out to community websites to request them to feature PsyOps on their web pages and encourage their members to participate in the research project.

Personality data was gathered by measuring the Big Five personality dimensions. The NEO-PI-R used in the research by Lankveld et al. [20], [21] demanded a high time investment of the participants. This would have negatively impacted requirement (1) as it would have limited the sample to people willing to invest 45-60 minutes in a personality test. Therefore, we decided to use the 100-item IPIP version of the Big Five which required 5-20 minutes of the participant's time. The test consisted of 100 statements that a participant was asked to grade on a 5-point Likert scale, indicating how much he felt the statement described his personality. Scores on the statements were collated into the same five personality dimensions as the NEO-PI-R, with one exception. While the NEO-PI-R measures Openness, Conscientiousness, Extraversion, Agreeableness, and *Neuroticism* (OCEA*N*), the IPIP measures the inverse of the last dimension and labels it *Emotional Stability* (OCEA-*ES*). The IPIP version is a validated instance of the Big Five Personality Inventory [10].

A. Data Collection

All data was automatically collected and stored via the PsyOps website. Data collection took place over a period of six weeks. During this time, participants could visit the website to submit their data. The data form contained six fields: age, player name, gaming platform, 100-item IPIP questionnaire, country of residence, and credits. The participant was asked to give permission for anonymous use of his game statistics, which were then automatically retrieved from a public database.[3] Player name was used as the key for game statistics retrieval. It is a unique identifier of a player account in Battlefield 3. Therefore, it was used to ensure that all participants were unique individuals. The credits field was a tick box where participants indicated if they wished to have their player name listed on the credits page of the final research report. After submitting all their data, participants were forwarded to a page showing their Big Five scores and an overview of what the different personality dimensions entail.

B. Data Analysis

Data analysis progressed in five steps.

1) Define integrity filters.
2) Determine play style based on game statistics.
3) Review the characteristics of the sample.
4) Calculate correlations between age and play style.
5) Determine percentage of variance in age explained by play style.

Below we will detail the reasoning and processes underlying each step. The Section IV (Results) is structured in the same manner.

(1) Only one filter was defined to maximize data integrity. The *age filter* was applied to age, excluding individuals indicating an age below 12 or above 65. Age values could be selected from 1 to 99, and some people might have entered the extreme or near-extreme values. To ensure the inclusion of the maximum number of participants, the limits were set to the onset of puberty (12) and end of working age (65). To maximize external validity, no further filters were used. The only relevant variable that was vulnerable to misreporting was age. Play style and platform could not be misreported as this data was drawn directly from the third-party statistics data base. Country of residence could have been misreported but would have had no effect on the research results.

(2) Play style was determined from a participant's game statistics. To gain a general understanding of the elements of game play shaping an individual's play style, a basic grasp of the game mechanics of Battlefield 3 is necessary. The following overview sketches the basic strategic options and objectives that players are offered in the game.

Battlefield 3 contains many strategical options. Five of the most prominent ones are briefly explained. First, a player selects one of three main game modes: Conquest, Rush, and Death Match. Each mode differs in game play, speed, and focus. However, all game modes may only be played as part of a team. Secondly, players select one of four roles to play in a match: Assault, Engineer, Support, and Recon. Thirdly, roles offer a limited and unique choice of support abilities (e.g., healing or reviving team mates, repairing vehicles, resupplying team mates, creating booby traps, or offering team mates reconnaissance services). Fourthly, roles offer a limited and unique choice of weapons. All weapons handle differently and are preferred for different play styles (e.g., close-range versus long-range). Fifthly, vehicles can be used as weapons or transport and are available to all players regardless of role.

Battlefield 3 traditionally sets players one single goal: to win the match. However, most players also strive to maximize kills, and acquire unlocks. Points are earned for reaching the goals, as well as for related subgoals such as playing objectives and providing support for the team. Self-sacrificing behavior such as giving support and staying behind to defend objectives, may help a team win, but damage someone's personal score. Additional points are awarded for kills based on team work (Savior Kills, Avenger Kills, Kill Assists, and Suppression Assists). Earning these points is conditional on two or more team members engaging one enemy. The intricacies of the game run even deeper, but this overview suffices to understand our research (See the IGN *Battlefield 3 Wiki Guide*[4] for more information.)

To determine the participant's play style, 826 game statistics were gathered. Domain knowledge was employed to combine and process the game statistics to reflect play style more accurately. The result was that 60 play style variables were defined over 4 categories. Almost all variables are ratios of 2 or more statistics to ensure that play style is measured independent of confounds. For instance, the absolute number of kills a person obtains is not informative until it is made relative to time played (speed of kills) or number of deaths (skill of the player). The 4 categories of play style variables were defined on the type of ratio used in the category. In the following overview, the number of variables per category is displayed in brackets. First, *Time* variables (26) are measures of actions per second played. Secondly, *Score* variables (13) are measures of the proportion of a certain score per total score. Thirdly, *Ratio* variables (16) are a group of unrelated variables that have been made relative to different criteria (e.g., Wins per Loss, Hits per Kill). Fourthly, *Absolute* variables (5) are measures that are tracked in absolute values instead of ratios (e.g., ELO rating.)

The 60 play style variables only reflect behaviors that every player can show at any time in the game. It does not follow that every behavior a player *can* exhibit *is* exhibited by each player. If a player never engages in a certain behavior, then he will show a missing value for the relevant play style

[3] http://bf3stats.com/

[4] http://www.ign.com/wikis/battlefield-3/Multiplayer

variable. We have chosen to enter 0 for missing values on play style variables. Lower values on play style variables generally indicate less skill with the relevant behavior. We consider it plausible that (barring a few exceptions) a player who never exhibits a certain behavior, has little to no skill with that behavior. Therefore, it follows that 0 is a representative value for play style variables with missing values.

(3) The characteristics of the sample were reviewed by looking at the data distributions of the six types of data collected. (1) Age distribution was plotted in a histogram. (2) Play style was reviewed in general terms, describing the overall means on key variables, as well as the character of the distributions. (3) Platform distribution was reviewed in absolute numbers. (4) Personality data was reflected in a box plot of the scores the participants achieved on each of the five personality dimensions. The scores were determined from the 100-item IPIP questionnaire. The IPIP data consisted of 100 variables with a value of $[1, 5]$, where 1 denoted "Very Inaccurate" and 5 denoted "Very Accurate." The values are attained through self-report. They reflect how much a participant identifies with a statement, such as "I love children." The Big Five scores were calculated from the IPIP data by combining the values on the statements that related to a particular dimension. The result was a value of $[20, 100]$ on each of the five personality dimensions. (5) Country of residence was summarized in a frequency table. (6) Credits answers were reviewed in absolute numbers.

(4) Pearson's Correlations were calculated between age and the play style variables. Correlations were considered significant at $\alpha < 0.01$.

(5) Multiple Linear Regression (MLR) was used to determine the percentage of variance in age that can be explained by play style. This was done for both the total sample, as well as for subsamples based on gaming platform. There are three possible values for gaming platform: PC, Xbox 360, and Playstation 3. Players on different gaming platforms cannot interact with each other. Gaming platform can influence the relationship between age and play style in three ways: (1) Platform preference might contain an inherent sample bias. (2) The interface is different between PC and the two consoles, and slightly different between the two consoles. (3) PC supports larger maps and higher server capacities than the two consoles.

Overall, the link between age and play style was explored on the basis of a large sample of data from individuals aged 12-65, reviewing 60 play style variables, and characterizing the sample on personality, country of residence, and the credits question. For a comprehensive insight into the statistical methods described above, we refer the reader to [8].

IV. Results

The final data set contained data from 13,376 participants. During the data collection phase, the third-party game statistics database was restructured to accommodate an upcoming expansion of the game. The restructuring process shifted the format of the collected data so only the first 9366 submissions were usable. The results will be discussed according to the 5 steps of data analysis outlined in the previous section.

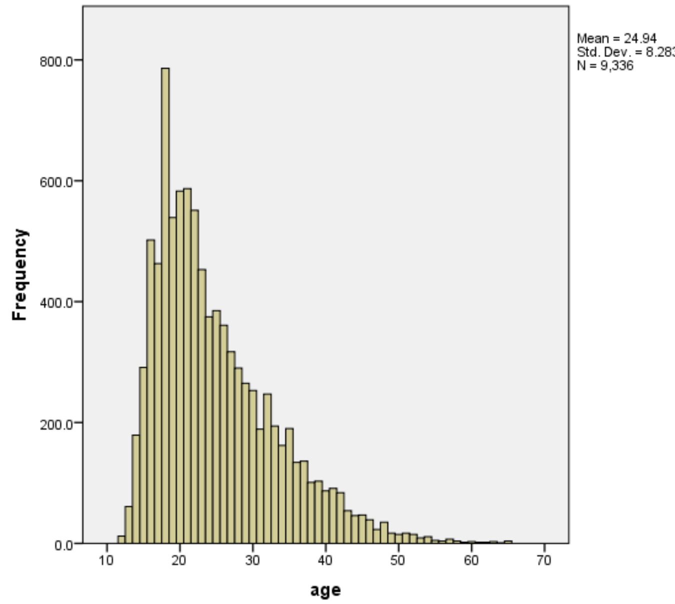

Fig. 1. Age Distribution

A. Step 1: Age Filter

The age filter excluded 31 participants who had indicated an age below 12 or above 65.

B. Step 2: Play Style Variables

The 60 play style variables can be viewed in Table II, which also shows the correlations discussed in Section IV-D. 1263 participants exhibited one or more missing values on the play style variables. Missing values were substituted with 0 as outlined in step 2 of the Data Analysis (Section III-B).

C. Step 3: Sample Characteristics

Age. The distribution of age in the sample can be seen in Figure 1. The distribution is a skewed normal distribution with an average of 25, and spread over all mature ages. From the age of 17 to 18 there is a noticeable dip followed by a spike. Battlefield 3 is a game rated 18+ in most countries. It is likely that some participants that were 17 years old reported their age as 18 due to the age threshold for the game. The distribution of age per gaming platform is similar. The average age per platform is 25.3 (PC), 24.22 (Xbox 360), and 25.12 (Playstation 3). The average age differs significantly between PC and Xbox 360, and Xbox 360 and Playstation 3. It does not differ significantly between PC and Playstation 3.

Play Style. Across the 60 play style variables (Table II), we highlight two key play style characteristics of the sample. First, the sample is biased toward more experienced and skilled players, with performance variables showing *means* above those of the Battlefield 3 populace. Secondly, the *distributions* of the play style variables are likely to be equal to those in the Battlefield 3 populace. Most variables are normally distributed over a wide range of values. The variables that are not normally distributed are probably not normally distributed in the Battlefield 3 populace either. For instance, some vehicles or classes are not used at all by some players, creating a peak

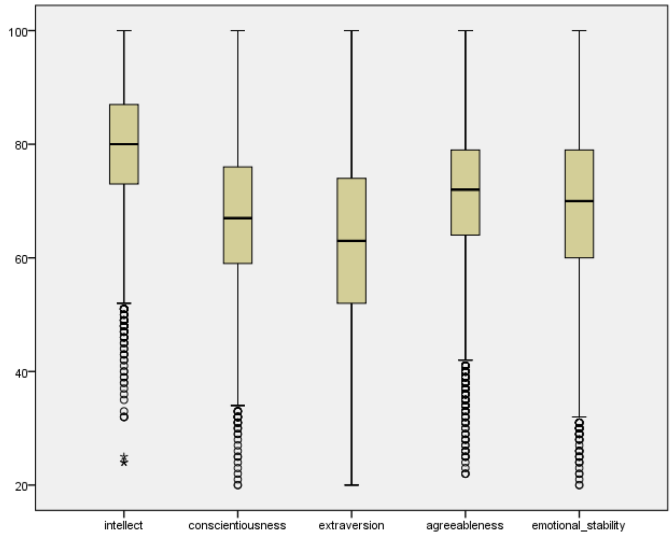

Fig. 2. Big 5 Distribution - The Y axis denotes the score on each of the personality dimensions

at the 0-point, while the average of the sample is significantly removed from 0. We consider it likely that such patterns exist in the Battlefield 3 populace as well. Therefore, the distribution of play style variables is considered representative of the Battlefield 3 populace (external validity), with the exception of a high performance bias.

Platform. Platform distribution is fairly even at 3725 PC players, 2564 Xbox 360 players, and 3047 Playstation 3 players.

Personality. Figure 2 shows the distribution of the scores the participants obtained on the IPIP. Scores on each of the dimensions can range from 20 to 100. The personality scores across the sample are high and cover a wide range of values. The high scores indicate a sample bias, while the wide range of values indicate high heterogeneity. Sample bias has a negative effect on external validity, while heterogeneity has a positive effect on external validity.

Country. Participants reported 90 different countries of residence. Table I shows the distribution for the 13 countries that were reported by at least 100 participants each (7893 in total). An additional 33 countries were reported by 10-99 participants per country, and 22 countries were reported by 2-9 participants per country. The remaining 22 countries were reported by 1 participant per country. There is a high likelihood that a participant misreported their country of residence if he is the only one reporting that country. No action was taken to exclude such cases, because misreported country of residence has no impact on the relationship between age and play style.

Credits. For the sake of completeness, the distribution of credits answers are reported. Credits values have no further bearing on the research into the relationship between age and play style. The distribution was as follows: 6765 participants answered 'yes', and 2571 participants answered 'no' when asked if they would like their player name to be mentioned in the credits of the research.

TABLE I. COUNTRY DISTRIBUTION

Country	N
United States	4039
United Kingdom	1099
Canada	499
Australia	403
Germany	371
Sweden	366
The Netherlands	266
Finland	229
South Africa	141
France	139
Russia	135
Brazil	106
Republic of Ireland	100

D. Step 4: Correlations

The correlations between age and play style can be found in Table II. The first column displays the names of the play style variables (See the IGN *Battlefield 3 Wiki Guide*[5] for more information on the game play elements described.) The second column displays the p values of the correlations with age. The p value describes the probability that a correlation occurs in the data by chance. The third column displays the r values (effect sizes) of the correlations with age. The r value describes the strength of a correlation using the interval $[-1, 1]$.

Of the 60 play style variables, 56 correlate significantly with age at a level of confidence of $\alpha < 0.01$, and 54 of these are even significant at $\alpha < 0.001$. The largest effect sizes can be found for Unlock Score per Total Time ($-.417$), Kills per Total Time ($-.368$), Savior and Avenger Kills per Total Time ($-.330$), and Assault Score per Assault Time ($-.319$). These four correlations are highlighted as examples of high effect sizes. In the Discussion (Section V) we offer a tentative interpretation of how age and play style are related. Yet, this is not the aim of our current research. The aim is to determine how much of the variance in age can be explained by play style. However, to give the reader an idea of the shape of the relationship between age and play style, we present the following five observations made from the correlations between age and play style variables.

1) Older players kill and die less. Age is negatively correlated with the frequency of both kills and deaths per time unit. Age is negatively correlated with accuracy, and positively correlated with Deaths per Kill.

2) Older players score less. Age is negatively correlated with all measures of score per time unit, with the exception of Objective Score.

3) Older players focus on winning. Age is negatively correlated to Wins per Loss, but with an effect size (-0.076) that is two to five times lower than would be expected given the correlations between age and the other two performance metrics (kills & score). Matches are won by gaining kills or performing actions that earn score. Score earned by performing actions directly related to winning, is counted as Objective Score. Objective Score is the only score variable that is not significantly correlated to age in a negative manner. Therefore it can be deduced that older players focus more on winning, but are not as skillful at the relevant actions necessary to win (observations 1 & 2).

[5]http://www.ign.com/wikis/battlefield-3/Multiplayer

TABLE II. AGE TO PLAY STYLE CORRELATIONS

Play Style Variable	p	r
Time.VehicleTimePerTotalTime	.004	-.030
Time.VehicleDestroyedPerTotalTime	<.000	-.146
Time.VehicleDestroyAssistPerTotalTime	<.000	-.111
Time.KillsPerTotalTime	<.000	-.368
Time.KillAssistPerTotalTime	<.000	-.263
Time.NemesisKillsPerTotalTime	<.000	-.217
Time.SaviorAvengerPerTotalTime	<.000	-.330
Time.DogTagsPerTotalTime	<.000	-.165
Time.DeathsPerTotalTime	<.000	-.164
Time.ShotsPerTotalTime	<.000	-.174
Time.GrenadeShotsPerTotalTime	.196	-.013
Time.SuppressionPerTotalTime	<.000	-.197
Time.ResuppliesPerSupportTime	.991	.000
Time.RevivesPerAssaultTime	<.000	-.236
Time.RepairsPerEngineerTime	<.000	-.126
Time.RadioBeaconSpawnsPerReconTime	.054	-.020
Time.SupportTimePerTotalTime	<.000	.164
Time.AssaultTimePerTotalTime	<.000	-.085
Time.ReconTimePerTotalTime	<.000	-.174
Time.EngineerTimePerTotalTime	<.000	.186
Time.VehicleMBTTimePerTotalTime	<.000	.221
Time.VehicleAHTimePerTotalTime	<.000	-.098
Time.VehicleAATimePerTotalTime	<.000	.072
Time.VehicleJetTimePerTotalTime	<.000	-.238
Time.VehicleSHTimePerTotalTime	<.000	-.172
Time.VehicleIFVTimePerTotalTime	<.000	.089
Ratio.DogTagsPerKill	<.000	-.061
Ratio.DeathsPerKill	<.000	.279
Ratio.WinsPerLoss	<.000	-.076
Ratio.MVP123PerRound	<.000	-.203
Ratio.AceSquadPerRound	<.000	-.075
Ratio.SaviorAvengerPerKill	<.000	-.063
Ratio.HitsPerKill	<.000	.087
Ratio.HitsPerShot	<.000	-.244
Ratio.HeadShotsPerShot	<.000	-.186
Ratio.GrenadeHitPerShot	<.000	-.140
Ratio.GrenadeKillsPerShot	<.000	-.137
Ratio.MComDefenseKillsPerMComDestroyed	<.000	.049
Ratio.FlagDefendKillsPerFlagCapture	<.000	-.104
Score.UnlockScorePerTotalTime	<.000	-.417
Score.ObjectiveScorePerTotalTime	.020	-.024
Score.ScorePerTotalTime	<.000	-.268
Score.TeamScorePerTotalTime	<.000	-.134
Score.SquadScorePerTotalTime	<.000	-.131
Score.SupportScorePerSupportTime	<.000	-.265
Score.AssaultScorePerAssaultTime	<.000	-.319
Score.EngineerScorePerEngineerTime	<.000	-.299
Score.ReconScorePerReconTime	<.000	-.274
Score.VehicleScorePerVehicleTime	<.000	-.050
Score.VehicleMBTScorePerVehicleMBTTime	<.000	-.173
Score.VehicleAAScorePerVehicleAATime	<.000	-.144
Score.VehicleSHScorePerVehicleSHTime	<.000	-.198
Score.VehicleIFVScorePerVehicleIFVTime	<.000	-.125
Score.VehicleAHScorePerVehicleAHTime	<.000	-.177
Score.VehicleJETScorePerVehicleJETTime	<.000	-.273
Absolute.TimeHours	<.000	.204
Absolute.Rank	.002	.032
Absolute.Elo	<.000	-.227
Absolute.LongestHS	<.000	-.107
Absolute.LongesthandHS	<.000	-.126

4) Older players invest more time in the game. Age is positively correlated with total play time. Further analysis shows play time to correlate *positively* with all measures of performance (kills, score, wins) with effect sizes around 0.2. The relationship runs counter to observations 1 and 2.

5) Age influences class and vehicle preferences. Age correlates positively with use of the Support and Engineer classes, and negatively with the Assault and Recon classes. Age correlates positively with use of the tank (MBT), while it correlates negatively with use of aircraft (jets & helicopters). Despite class and vehicle preferences, younger players score better with all classes and vehicles (observation 2).

The five observations indicate the complexity of the relationship between age and play style. The next section reports how much of the variance in age can be explained by play style.

E. Step 5: Multiple Linear Regression

In the total sample, 45.7% of the variance in age can be explained by 46 play style variables. This was determined by running a multiple linear regression with age as the dependent variable, and the 60 play style variables as independent variables. Backward selection removed 14 play style variables under an entry condition of 0.005, and a removal condition of 0.01. The conditions were a factor 10 stricter than is usual. Therefore, the remaining 46 variables in the model are significant with a maximum of $p = 0.01$. ANOVA shows the model itself to be highly significant at $p = 0.00$.

Using the same procedure on the subsamples based on platform, we find the following. For PC players, 43.1% of the variance in age can be explained using 31 play style variables. For Xbox 360 players, 53.9% of the variance in age can be explained using 30 variables. For Playstation 3 players, 51.7% of the variance can be explained using 28 play style variables. All models are significant at $p = 0.00$.

It falls outside the scope of the current research to explore the exact shape of the regression models. However, it is interesting to note that dividing the sample along gaming platform generates models with only two thirds of the number of variables used for the model of the full sample.

V. DISCUSSION

Our findings show that a strong link exists between age and play style. This section will discuss five major aspects of our research. First, the external validity of our findings are analyzed (Section V-A). Secondly, the relevance of our findings is discussed (Section V-B). Thirdly, an interpretation of the results is offered (Section V-C). Fourthly, an exploration of future work is presented (Section V-D). Fifthly, two suggestions for applications of the results are made (Section V-E).

A. External Validity

The external validity of our study is high despite the sample bias toward expert players. The bias is off-set by the size and heterogeneity (age, personality, country of residence) of the sample. Additionally, the distributions of the play style variables are the same as to be expected in the general populace, and shows a wide spread, also covering the range of less skilled players.

The sample bias occurred due to the method of participant recruitment. The most feasible approach to reaching out to and enthusing a large group of gamers for our research, was to address those that are already deeply invested in the game. Players with lower investment in the game are by definition less likely to involve themselves with game-related actions outside of direct play, and are therefore hard to find and reach. Arguably, they would also have been less likely to invest their time in the research even if they did know of it.

It is an open question whether the expertise level of the players mediates the relationship between age and play style.

Findings by Iida et al. [12] suggest that expert players are more likely to have meaningful play styles, while novices are more likely to exhibit play styles focused on exploration and experimentation. Creating and testing a model of the relationship between age and play style would shed light on this issue.

B. Relevance

The relevance of our findings is high due to the strength of the relationship between age and play style. Using MLR, about half the variance in age can be explained by play style. In other words, the correlation between the model generated by the MLR and age has an effect size of around 0.7. Cohen classifies such an effect size as 'large' [4].

C. Interpretation

The nature of the link between age and play style is a matter of debate. The additional analysis of correlations gives some insight into the form of the link. Here we venture our interpretation of the correlations between age and play style, based on the three bridging constructs presented in the Related Work (Section II).

Cognitive Performance in the form of spatial cognition, memory, learning, and attention declines with age. The result is that older players play less effectively and more slowly than younger players. Older players score less and earn fewer kills. Additionally, they adapt their play style to their speed of play by picking vehicles that focus on slower game play.

Motivation for Achievement declines with age. The result is that older players perform worse in the game in terms of kills and score.

Personality shifts toward increased Conscientiousness with age. The result is that older players play more slowly and focus on their 'responsibilities' in the game (winning).

All three bridging constructs help explain the decrease in performance and speed of play for the older players. The increased focus on winning that comes with age, is in line with the increase in Conscientiousness. Differences in preference patterns (i.e. classes) do not clearly conform to the three bridging constructs.

D. Future Work

For future work, the MLR should be repeated with two major additions. First, it is recommended to check collinearity. It was not checked in our current analysis. Collinearity does not have a great influence on variance explained, but has a high impact on how coefficients should be interpreted. Secondly, after checking collinearity, coefficients can be correctly interpreted. The coefficients give insight into how (much) different variables contribute to the explanation of variance in age. An MLR with these two additions will offer insight into how each play style variable contributes to the explanation of variance in age. The insight can then be used to create a model of the connection between age and play style. Such a model should be created to represent the link between age and play style over all video games. As was set out in the Related Work (Section II), we expect that the main factors in the model will be cognitive performance, motivation, and personality. Our work in this area so far can be found in [18].

Additionally, new data sets could be obtained to further explore the link between age and play style. We recommend statistical methods for data analysis. We have applied machine learning techniques to the current data set, but this did not yield interesting results.

E. Applications

The link between age and play style can be used to create more accurate player models. Our findings show that play style changes with age. We suggest two possible applications of our findings. First, player models will be more accurate if they control for age. The following example illustrates this. It might be the case that younger and older players respond differently to difficulty increases in a game, even though both groups of players are at the same initial skill level. It might be so that an older player would respond favorably to a difficulty increase despite his low skill level, because he values other aspects of the game more than performance. He might savor a challenge or feel more motivated when the game "ups the ante". In contrast, it is conceivable that a younger player with a low performance would find an increase of difficulty discouraging and give up on the game all together.

Secondly, being able to determine someone's age from their play style opens up the opportunity to create tweaks to game mechanics that were not possible before. For instance, an RPG might create a back story for a player based on his behavior in an introduction level. Imagine a game that accurately deduces the age of the player from the player's behavior. Such a game could increase the player's immersion by creating a more relatable back story for the player.

VI. Conclusion

Our aim was to answer the question: *How much of the variance in age can be explained by play style?* The answer is that 45.7% of the variance in age can be explained by 46 play style variables. Additionally, when the sample is divided along gaming platform we see the following: (PC) 43.1% by 31 variables, (Xbox 360) 53.9% by 30 variables, and (Playstation 3) 51.7% by 28 variables. Our findings have a high external validity due to the large and heterogeneous nature of the sample we acquired through an elaborate promotional campaign (PsyOps). The strength of the relationship between age and play style is classified as 'large' according to Cohen [4]. As such, our findings indicate that player models can benefit greatly from incorporating age as a predictive or controlling variable. Future work will focus on determining the exact contributions of different components of play style in explaining the variance in age. We expect that cognitive performance, motivation, and personality form the link between age and play style.

The complete PsyOps data set can be downloaded at http://www.psyopsresearch.com/download/

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