Past Our Prime: A Study of Age & Play Style Development in Battlefield 3

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Abstract

In recent decades video games have come to appeal to people of all ages. The effect of age on how people play games is not fully understood. In this paper we delve into the question how age relates to an individual's play style. 'Play style' is defined as any (set of) patterns in game actions performed by a player. Based on data from 10,416 *Battlefield 3* players, we found that age strongly correlates to how people start out playing a game (initial play style), and to how they change their play style over time (play style development). Our data shows three major trends: (1) correlations between age and initial play style peak around the age of 20; (2) performance decreases with age; and (3) speed of play decreases with age. The relationship between age and play style may be explained by the neuro-cognitive effects of aging: as people grow older, their cognitive performance decays, their personalities shift to a more conscientious style, and their gaming motivations become less achievement-oriented.

Index Terms

User Modeling, Multiplayer Games

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I. INTRODUCTION

IN the past, video games were stigmatized as child's play [1]. Nowadays, the medium has matured into a pastime for everyone, regardless of age [2]. The Entertainment Software Association reflects this fact, reporting that in 2013 58% of Americans played video games. Their average age stood at 30, while 68% of gamers were 18 years or older.[1] Despite the recent shift in the age of the gamer demographic [1], the relationship between age and how people play games has remained largely unexplored. Age is known to influence many facets of human behavior, such as the purchase patterns of consumers [3]. In this paper we endeavor to find out if age exerts a similar influence on an individual's play style.

Aging causes changes in cognition, personality, and motivation. It is accompanied by a decline in cognitive performance, a shift to a more conscientious personality, and a decrease in achievement-based gaming motivation (see Section II). We expect that the effects of aging impact how an individual *is able* and *is willing* to play a video game. The impact would be visible in an individual's *play style*. We define 'play style' as the patterns in the game actions performed by a player. **'Play style variables' track the frequency and proportion of an individual's game actions. Other authors use alternative terminology for similar constructs, cf. [4], [5], [6], [7]. Due to a lack of consensus on a definitive terminology, we will adhere to the term 'play style' as a generic and intuitive term.**

If the relationship between age and play style is robust, then game developers would be able to utilize age and play style data for two purposes: adaptive game play, and marketing research. First, if age and play style are related, then *age* data can be used to adapt the game play experience of an individual to cater to his play style. Secondly, if age and play style are related, then *play style* data can be used to deduce the age of the player to gather data for marketing research. **Both these purposes fall within the broader field of player modeling [8], [9], [7], [6].**

Our goal is to determine whether age and play style are indeed related. To achieve our goal, we set out to answer the research question: *How does a player's age relate to his play style?* To answer this question we will first review the relevant background literature (Section II). Secondly, we will outline the methods employed in our research (Section III). Thirdly, we report the findings of the study we conducted among 10,416 *Battlefield 3* players (Section IV). Fourthly, we will discuss the generalizibility and implications of our findings (Section V). Lastly, we summarize our findings (Section VI).

II. BACKGROUND

In an exploratory study by Tekofsky et al. [10] among 9,367 *Battlefield 3* players it was found that age and play style correlate at medium effect sizes ($.1 < r < .3$). Younger players[2] play faster and perform better at the game. Younger and older players show different patterns in class and vehicle preferences. Furthermore, it was shown that 45.7% of the variance in age (dependent variable) could be explained by 46 play style variables (independent variables). The main limitation of the study was that it relied on play style data collected at one point in time, describing the cumulative achievements of the participant over his entire game career. The data neither describes play style development over time, nor does it control for the time a player has spent in the game.

In this paper we delve further into how age and play style are connected. **Guarente [11] recently summarized the scientific literature on aging, pointing out that the effects of aging are myriad, and only partly understood. The biological mechanisms of aging (e.g., telomere shortening, stem cell depletion, mitochondrial disfunction) fall outside the scope of our research. We** will focus on three interrelated neuro-cognitive factors that relate age to play style: *cognitive performance*, *motivation*, and *personality*. Though all three are intertwined [12], they merit separate consideration as previous research has shown that each relates to both age and play style in its own unique way. In the discussion of each factor, we first offer a rigid definition of the subject area, followed by a short review of how that factor relates to *age* and *play style*, respectively.

A. Cognitive Performance

We define *cognitive performance* as an individual's performance on tasks that test his *cognitive processes*, such as perception, memory, and abstract thinking.

Age is accompanied by a deterioration in cognitive performance. We provide three examples of cognitive decline and how they relate to gaming [13]. First, age is negatively correlated with performance on various components of spatial tasks [14], such as spatial pattern completion [15], and spatial memory [16]. Spatial skills are relevant for efficient navigation of a game world. Secondly, age is negatively correlated with learning and memory skills in general [17]. Both learning and memory skills are crucial in mastering game mechanics and

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[1]April, 2013: http://www.theesa.com

[2]**Throughout this paper the terms 'younger players' and 'older players' are used in a comparative instead of an absolute sense. The terms are intended to describe trends that exist between any two players with an age difference. The use of comparative qualifiers of age allows us to make general claims about the trends in the population. We will indicate specific age brackets for certain findings where ever these can be specified in absolute terms.**

completing tasks in video games. Thirdly, age is negatively correlated with performance on attentional tasks [18]. 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 has only been linked to cognitive performance in one manner: how improvements in game performance (the player's effectiveness at fulfilling the goals of the game) lead to improvements in cognitive performance. Green and Bavelier [19] reported multiple cognitive performance improvements due to video game training, such as improvements in spatial cognition and attention. Chandramallika et al. [20] 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 processes, including memory.

B. Motivation

Humphreys and Revelle [12] define motivation as "a hypothetical construct that has traditionally been used to describe and explain differences in intensity and direction of behavior. It is the state that results from a combination of individual needs and desires with the stimulus properties of the situation."

Age correlates with motivations for gaming. Yee [21], [5] conducted research into the motivations of a large sample (3000+) of massively multiplayer online role-playing game (MMORPG) players. He found that motivations for gaming cluster into three categories: Achievement, Social, and Immersion. Each motivation consists of three or four components. Achievement motivation consists of the Advancement, Mechanics, and Competition components. Social motivation consists of the Socializing, Relationship, and Team Work components. Immersion motivation consists of the Discovery, Role-Playing, Customization, and Escapism components. The scores for all three motivations decrease significantly with age. Achievement motivation decreases moderately with age, while Social and Imersion motivations decrease slightly with age.

Play Style has not been linked to motivation in any of the literature we have found. Yee's findings do contain indirect measures that combine motivations and play style [5]. He measured gaming motivations by asking participants how they enjoyed different game play elements. By definition (see above) motivation shapes one's actions. Therefore, Yee's work contains an implicit link between play style and the Achievement, Social, and Immersion motivations in gaming.

C. Personality

Personality is made up of a number of *personality traits*. Humprey and Revelle [12] define personality traits as "convenient summaries of consistent behaviors across different situations". Personality is commonly determined by applying a *personality inventory*. We discuss personality in terms of the *Big Five personality inventory* [22]. The Big Five defines personality along the following dimensions: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

Age has been found to be significantly correlated to personality in large cross-cultural samples. McCrae et al. [23]

and Donnellan and Lucas [24] investigated the relationship between age and personality with a total of over 40,000 test subjects over 6 countries. They found that Extraversion and Openness decrease with age, while Agreeableness and Conscientiousness increase (limited to late middle age, see [24]). Neuroticism decreased with age in all countries but one (Germany).

Play Style correlates significantly with personality [25], [26]. Lankveld et al. [27], [28] found correlations between play style and Extraversion within small sample sizes. We continued the exploration of the link between play style and personality in a previous study [29]. It confirmed the relationship between play style and personality [29] in a sample of 6373 *Battlefield 3* players. 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).

III. METHODS

The current study is intended to provide a deeper look into how age influences play style. It can be characterized as a short-term, retrospective, longitudinal study among *Battlefield 3* players. We consider *Battlefield 3* a representative game of the most popular subgenre of video games. The game has sold 16.5 million copies.[3] It is among the most played games in the *Shooter* genre, which makes up 21.2% of video game sales in America.[4]

We have collected data on participants' play style over a period of 2 years (24 months). Some players will have played during the full 2 years, while other players may have only been involved in the game for a short period of time. Play length, frequency, and behavior all occurred naturalistically, without any intervention from the authors of this paper.

The data was analyzed using Regression Coefficient Analysis (RCA) [30], [31]. RCA broadly consists of performing regression analysis on a set of variables, and subsequently performing an additional analysis on the beta coefficients of the regression. We performed regression (line of best fit) of each play style variable (outcome variable) per individual against his play time (predictor variable). Secondly, we analyzed the beta coefficients (slope and intercept) by calculating the Pearson's correlation of age and the average beta coefficients per age group. We decided to use RCA instead of more sophisticated analysis methods. It is a straight-forward and insightful analysis that provides sufficient depth to answer our research question, cf. [32], [33], [34], [35], [36], [37], [38].

The data analysis procedure will be described in four parts. First, the method of data collection is described (Section III-A). Secondly, the manner of play style quantification is explained (Section III-B). Thirdly, the process of feature

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[3]March 22, 2014: http://www.vgchartz.com
[4]April, 2013: http://www.theesa.com

extraction is discussed (Section III-C). Fourthly, the statistical techniques used in the data analysis are reviewed (Section III-D).

A. Data Collection

The current data set is an extension of the data set used in previous work [10]. The previous data set was constructed as follows. All data was automatically collected and stored via the research website ('PsyOps'). Data collection took place over a period of six weeks in the summer of 2012, 8 months after release of the game. During this time, participants could visit the website to submit their data. Six fields were requested: age, player name, gaming platform, the 100-item IPIP[5] 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.[6] Player name was used as the key for game statistics retrieval. It is a unique identifier of a player account in *Battlefield 3* and 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. In total, 13,367 participants submitted their data.

The player names from the previous study were used as keys for the extraction of the longitudinal data in the current study. The original data only contained a snap shot ('history entry') of player behavior at one point in time, 8 months after release of *Battlefield 3*. For the current research we extracted all history entries per participant from the release of the game up until the time of data extraction, 2 years later. Each entry is a snap shot of a player's play style at the moment that entry was made. However, a string of entries for a particular player shows the development of play style over time. Participant data was only extracted if at least 2 history entries were available. The history entries were successfully extracted for 10,942 of the 13,367 participants. The history entries of the remaining 2,425 participants were not extracted. Their history entries could either not be found (i.e., they had changed their player name), were not sufficient for the purposes of our research (i.e., fewer than 2 history entries), or were corrupted.

B. Play Style Quantification

1) Game Play Description: To gain a general understanding of the elements of game play that shape an individual's play style, a basic grasp of the game mechanics of the relevant game, *Battlefield 3*, is necessary. The following overview sketches the basic strategic options and challenges that players are offered in the game.

We distinguish five major strategic options in *Battlefield 3*: (1) *Game mode selection*: 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. (2) *Role selection*: players select one of four roles to play in a match: Assault, Engineer, Support, and Recon. (3) *Support ability selection*: 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). (4) *Choice of weapons*: 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). (5) *Vehicle selection*: vehicles can be used as weapons or transport and are available to all players regardless of their role.

The challenges offered to the player in *Battlefield 3* are varied. Traditionally, *Battlefield 3* sets players one core challenge: to win the match. However, most players also strive to maximize kills, and acquire 'unlocks.' Points are earned for progress toward each challenge, as well as for related subchallenges, 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 may damage someone's personal score. Additional points are awarded for kills based on team work (Savior Kills, Avenger Kills, Kill Assists, and Suppression Assists). The intricacies of the game run even deeper, but this overview suffices to understand our research (see the IGN *Battlefield 3 Wiki Guide*[7] for more information.)

2) Data Description: In our research we define *play style* as any (set of) patterns in game actions performed by a player. *Battlefield 3* offers the player a wide set of game actions. We make a distinction between *free* and *locked* game actions. Game actions are *free* when they are *not* dependent of unlockable game assets. Game actions are *locked* when they are dependent of unlockable game assets. We only include free game actions in our play style analysis in order to compare participants fairly.

For each player all 826 available game variables were collected. In order to adhere to our definition of play style, we extracted a set of 59 play style variables that described *patterns* in *free* game actions performed by the player. In order to reflect *patterns*, all play style variables were ratios of two of the following types of variables: *Action*, *Score*, and *Time*.

Action variables (38) count how often a certain game action has been performed by a player. The vast majority of game actions are *locked*, such as the usage of unlockable guns or support abilities. The set of *free* game actions in *Battlefield 3* is 38.

Score variables (16) count how much a player has earned of a certain type of score. Each type of score is earned by a set of actions related to the type. For instance, Engineer Score is earned by using Engineer-specific equipment and guns, while Objective Score is earned by performing game actions directly related to the objective of the game mode. *Battlefield 3* distinguishes between 16 types of score.

Time variables (11) count how much time a player has spent on a certain activity. *Battlefield 3* tracks 11 types of time

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[5]International Personality Item Pool, http://ipip.ori.org/

[6]http://bf3stats.com/

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

variables, such time spent in a particular vehicle or time spent playing a particular class.

The 65 Action, Score, and Time variables each track the sum total of actions, score or time a player has accumulated for that particular variable. To extract information about play style, the 65 variables were converted into 59 ratio variables by dividing Action, Score and Time variables with each other where relevant. There are six unique permutations (called *categories*) for the division of Action, Score, and Time variables: Action over Action, Action over Score, Action over Time, Score over Time, Score over Score, and Time over Time. **Action over Score variables were not included. They describe the points that are scored by performing certain actions. Points per action is a fixed value in the game and thus not descriptive of play style.**

The remaining five categories are descriptive of play style in the following manner. (1) *Action over Action* variables describe a player's preference and skill at performing certain actions, such as how often he chooses to defend an objective instead of attack it, or how often he wins a round per time he loses one. (2) *Action over Time* variables describe the frequency with which a player performs different actions. (3) *Score over Time* variables describe the rate at which a player earns a certain type of points, such as objective or team score points. (4) *Score over Score* variables describe the proportional distribution of the different types of score a player earns. (5) *Time over Time* variables describe what actions the player prefers to spend time on.

All 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* actually 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 variable at that time. However, a player may not show a certain type of behavior early in his game career, but can exhibit it later on. Therefore, if a player shows a missing value on a certain variable at a certain time, that time point is discarded for that variable.

C. Feature Extraction

Two features were extracted per play style variable: the slope (s) and the intercept (i). The slope signifies the improvement of the participant over time on the relevant play style variable. The intercept signifies the starting point of the participant on the relevant play style variable. The slope and intercept are determined as follows. Each participant has a number of history entries. History entries are snap shots of a player's play style variables at a certain point in time. Such snap shots are made automatically when players view their profile on a particular website where they can view their game statistics.[5] The result is a set of irregular time series data: each player has a different number of history entries with a different distribution over time. **The number and distribution of history entries only relates to how often and when the participant visits the statistics website. They do not correspond to play time or play frequency.**

Per play style variable, per participant, the line of best fit is determined (regression). The line of best fit is defined by its slope and intercept (beta coefficients). It is relevant to note that the intercept is a hypothetical, extrapolated value that corresponds to neither the first history entry, nor to the actual value of the play style variable at time zero. However, the first history entry is not informative as starting point as each participant has their first history entry at a different time. The actual value of the play style variable at time zero is also not informative because this value is zero for everyone (no actions have been performed). This leaves the intercept as the best estimate of the value of a play style variable as if the participant had started the game performing in line with subsequent history entries. Together, the slope and intercept of the play style variables of an individual constitute a within-subject analysis.

The line of best fit for an age group is determined by taking the mean of the slope and the mean of the intercept of all the participants that fall within that age group. **By using the mean values all participants contribute equally to the line of best fit for a particular age group, and each age group contributes equally in the subsequent analysis of play style development.** Thus, each age group contains 59 pairs consisting of one slope and one intercept (one pair per play style variable). Age groups are defined by year (i.e., 20, 21, and 22 year olds all have their own age group). Each age group must consist of sufficient participants to be a representative sample of that age group. We have settled on a generous minimum of 100 participants per age group.

When referring to the specific age of a participant there is a 2 year time window related to our age measurement. The play style data was gathered over a period of 2 years. The age measurement took place 8 months into this period. So if a participant is reported to be of age x, then he was either of age $x - 1$ to age $x + 1$, or age x to age $x + 2$ during the 2 year research period. The two cases cannot be discerned from each other as we have not tracked specific birth dates in our data set. The time window does not impact the data analysis, because age data is accurately measured in a relative sense. Additionally, we will largely discuss our findings in terms of age brackets consisting of three of more age groups (see Section IV-B).

D. Statistical Methods

Each individual contributed to the mean intercept and mean slope for each variable for their age group. There are only as many data points per variable as there are age groups. Therefore, considering the human age range, the sample size is small. **RCA was performed by calculating the Pearson's r for age on the one hand**, and the slope and intercept of each variable per age group on the other hand.

Care should be taken when interpreting the correlations between age and the slope of a variable. The slope of a variable signifies the *speed at which the variable changes*. In our study, a correlation between age and the slope of a variable signifies the *acceleration* of the change in a variable over the span of years that people age. A negative correlation indicates a negative acceleration and a positive correlation indicates a positive acceleration. We consider two examples.

Fig. 1. A hypothetical example of a positive correlation between age and the slope of a play style variable. The slope values for all age groups are positive. Therefore, the positive correlation means that players increase their values on the relevant play style variable more quickly as they age.

Fig. 2. Age Distribution in the Sample: All age groups with less than 100 participants (below the horizontal line) were excluded.

First, Figure 1 illustrates a positive correlation between age and the slope of a play style variable. Slope values are positive for both young and old players. Four data points are highlighted to illustrate the progression of the slope values for the different age groups. Note how a positive correlation between age and the slope of a variable means that players increase their values on a play style variable more rapidly as they age. It does not mean that older players score higher on the relevant variable than younger players. To determine who scores the highest on a relevant variable, both the slope and intercept of a variable need to be combined. The slope of a variable only describes the *increase* (or *decrease*) of that variable over time. As such, slope is a measure of play style development over time. The correlation between the slope of a variable and age indicates the acceleration of the play style development over time in relation to age.

Secondly, we consider the following example. A variable has a negative acceleration over the years. What can be concluded from that? It means that younger people display a higher slope than older people (i.e., younger people increase more on this variable than older people). The information is about the relationship between the slopes of younger and older people. It does not tell us what direction the slopes run in. All slopes might be either negative or positive, or the slopes might run from positive to negative with age. It cannot be that the slopes run from negative to positive, as this would indicate a positive correlation. To alleviate the ambiguity of the development of the slope direction over the years, the direction of the slope (positive/negative) will be indicated for both young and old people for every significant correlation presented in our results.

IV. RESULTS

In this section we first review the characteristics of our sample in terms of age, play style, and **heterogeneity** (Section IV-A). Secondly, we present the findings from the **Regression Coefficient Analysis** (Section IV-B). Lastly, we discuss the patterns in our findings (Section IV-C).
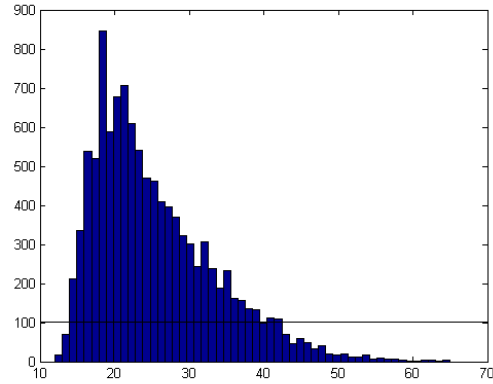
A. Sample Characteristics

Age: Figure 2 shows the age distribution in the sample. It is a skewed normal distribution with a mean of 25.2 and a standard deviation of 8.3. The number of participants per age group increases monotonically from the age of 12 to 21, with the exception of the 17 and 18 year olds. There are fewer 17 years olds than expected, and more 18 year olds than expected. As *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 age groups under the horizontal line in Figure 2 contain less than 100 participants. The cut-off points are 14 and 42. As a result, 526 participants with an age below 14 or above 42 were excluded from the sample. The remaining sample contained 10,416 participants. The exclusion was found to have no noticeable effects on the main results.

Play Style: We highlight two characteristics across the 59 play style variables. 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 a mix of normal distributions and zero-inflated distributions. Most variables are normally distributed over a wide range of values. Zero-inflated distributions are shown for play style variables that quantify in-game actions that do not necessarily have to be executed by every player.**

Heterogeneous Sample: The sample is quite **heterogeneous** in terms of the distribution of gaming platform, personality, and country of residence. Platform distribution is fairly even at 3895 PC players, 2946 Xbox 360 players, and 3575 Playstation 3 players. Figure 3 displays the distribution of personality scores in the sample. In our sample the scores on the Big Five are high, but 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.
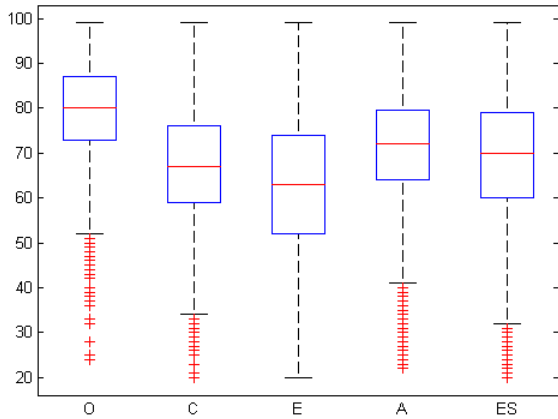
Fig. 3. Big 5 Distribution: The Y axis denotes the score distribution in the sample on each of the personality dimensions. The X-axis denotes the personality dimensions: O = Openness, C = Conscientiousness, E = Extraversion, A = Agreeableness, ES = Emotional Stability

B. Regression Coefficient Analysis

The correlations between age and play style can be found in Table I. The first column displays the names of the play style variables (see the IGN *Battlefield 3 Wiki Guide*[8] for more information on the game play elements described). The second column displays the Pearson's r of the correlation between age and the slope (s) of the relevant variable ($r(s)$). Each significant slope correlation is followed by two arrows, either of one points either up or down. The first arrow indicates if the slope is positive ($\uparrow$) or negative ($\downarrow$) for younger players. The second arrow indicates if the slope is positive ($\uparrow$) or negative ($\downarrow$) for older players. Most slope correlations describe an increase or decrease in a uniformly positive ($\uparrow\uparrow$) or negative ($\downarrow\downarrow$) slope. Some correlations describe a change from positive to negative ($\uparrow\downarrow$) slope or vice versa ($\downarrow\uparrow$). The arrows indicate which is the case. In one case (VehicleAHScorePerVehicleAHTime), indicated with ??, it is unclear from the distribution of the data if the relationship between the play style variable and age is positive or negative, as all the values are scattered around the zero-point. The third column displays the Pearson's r of the correlation between age and the intercept (i) of the relevant variable ($r(i)$). The r value describes the strength of a correlation using the interval $[-1, 1]$. The r value is only displayed if the variable has a significant correlation with age at $\alpha = .01$. In one case (KillAssistsPerTotalTime) there was not sufficient data available to calculate Pearson's r. The $r(s)$ and $r(i)$ for KillAssistsPerTotalTime is indicated with a '—'

A significant correlation is assumed to model a linear relationship (definition of Pearson's r). However, some of the distributions of slope and intercept values were non-linear. A typical pattern observed is the peaking of values within certain age brackets. In order to describe the results more concisely, we define the following age brackets: *middle teens* (age 14-16), *late teens* (age 17-19), *early twenties* (20-22), *middle-to-*

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

TABLE I
AGE TO PLAY STYLE CORRELATIONS: EFFECT SIZES (r) ARE DISPLAYED FOR THE SLOPE (s) AND INTERCEPT (i) OF PLAY STYLE VARIABLES THAT CORRELATE SIGNIFICANTLY WITH AGE AT $\alpha = 0.01$. ARROWS INDICATE THE DIRECTION OF THE SLOPE OF A VARIABLE FOR YOUNG AND OLD PLAYERS, RESPECTIVELY, WITH $\uparrow$ INDICATING A POSITIVE SLOPE AND $\downarrow$ INDICATING A NEGATIVE SLOPE. THE $\triangle$ INDICATES A SIGNIFICANT CORRELATION THAT PEAKS FOR PARTICIPANTS WHO ARE EITHER IN THEIR LATE TEENS OR EARLY TWENTIES.

Play Style Variable	Longitudinal			
	$r(s)$		$r(i)$	
Action over Action Variables, range [-Inf, Inf]				
DeathsPerKill	-.84	↓↓ △	.89	△
WinsPerLoss			-.75	△
MVP123PerRound	.53	↑↑	-.86	△
AceSquadPerRound	.59	↑↑	-.54	△
HitsPerKill			.67	
HitsPerShot			-.87	△
HeadShotsPerShot			-.90	△
DogTagsPerKill			-.97	
SaviorAvengerPerKill	.88	↑↑	-.54	△
GrenadeHitsPerShot			-.81	△
GrenadeKillsPerShot	-.65	↑↓	-.76	△
MComDefenseKillsPerMComDestroyed			.67	
FlagDefenseKillsPerFlagCapture			-.73	△
Action over Time Variables, range [0, Inf]				
VehicleDestroyedPerTotalTime	-.66	↑↑	-.85	△
VehicleDestroyAssistsPerTotalTime			-.73	
KillsPerTotalTime	-.51	↑↑	-.97	△
KillAssistsPerTotalTime	—		—	
NemesisKillsPerTotalTime	-.96	↑↑	-.97	△
SaviorAvengerKillsPerTotalTime	-.53	↑↑	-.98	
DogTagsPerTotalTime			-.97	
DeathsPerTotalTime	.72	↑↑	-.79	
ShotsPerTotalTime	.62	↑↑	-.94	△
GrenadeShotsPerTotalTime	.85	↑↑		
SuppressionPerTotalTime	.53	↑↑	-.96	
ResuppliesPerSupportTime	.49	↑↑		
RevivesPerAssaultTime	.81	↑↑	-.97	
RepairsPerEngineerTime			-.88	
RadioBeaconSpawnsPerReconTime	.67	↑↑		
Score over Time Variables, range [0, Inf]				
ScorePerTotalTime	-.72	↑↑	-.94	△
UnlockScorePerTotalTime	.71	↓↓ △	-.98	
ObjectiveScorePerTotalTime				
TeamScorePerTotalTime	.74	↑↑	-.93	△
SquadScorePerTotalTime			-.89	△
SupportScorePerSupportTime			-.96	△
AssaultScorePerAssaultTime			-.98	△
EngineerScorePerEngineerTime	-.48	↑↑	-.97	△
ReconScorePerReconTime			-.95	△
VehicleScorePerVehicleTime			-.47	△
VehicleMBTScorePerVehicleMBTTime			-.84	△
VehicleAAScorePerVehicleAATime			-.93	△
VehicleSHScorePerVehicleSHTime			-.91	△
VehicleIFVScorePerVehicleIFVTime			-.81	△
VehicleAHScorePerVehicleAHTime	-.56	??	-.90	△
VehicleJetScorePerVehicleJetTime			-.53	
Score over Score Variables, range [0,1]				
UnlockScorePerScore	.58	↓↓	-.87	
ObjectiveScorePerScore	-.91	↓↓ △	.94	△
TeamScorePerScore	.94	↓↑	-.60	
SquadScorePerScore			.87	
Time over Time Variables, range [0,1]				
SupportTimePerTotalTime			.93	
AssaultTimePerTotalTime	-.65	↑↑	-.60	
ReconTimePerTotalTime			-.83	△
EngineerTimePerTotalTime	-.91	↑↑	.98	
VehicleTimePerTotalTime	-.60	↑↑	-.70	
VehicleMBTTimePerTotalTime			.80	
VehicleAHTimePerTotalTime				
VehicleAATimePerTotalTime	.54	↑↑	.67	
VehicleJetTimePerTotalTime	-.80	↑↑	-.81	
VehicleSHTimePerTotalTime				
VehicleIFVTimePerTotalTime	.60	↑↑		

late twenties (23-29), and *thirty plus* (30-42). Variables **with significant correlations** that peak at a certain age, did so in either the late teens or early twenties. In those cases, the shape of the scatter plot is an asymmetrical (inverted) v-shape, with the long edge covering the higher age groups (older than late teens or early twenties), and the short edge covering the lower age groups (younger than late teens or early twenties). When this is the case, a variable is denoted with a $\triangle$ symbol (see Figures 4 and 5 for examples).

The skewedness of the distribution of age did not meaningfully impact the results. Although there exists a debate around the importance of the normality assumption for the Pearsons correlational analysis [39], we decided to err on the side of caution and repeated our analysis with the Spearmans test. While Pearsons r is generally considered a parametric test of linearity, Spearmans ρ is a non-parametric test of monotonicity, which does not require an assumption of normality. The results from the Spearmans test can be found in Table II in the Appendix. The substantial overlap in the effect sizes and significant correlations between the Spearmans and Person's indices indicates the validity of the values we report for Pearsons r.

Table I shows that 81 of the 118 potential correlations are significant. At $\alpha = .01$ only 1 in 100 significant correlations are expected to be spurious. However, play style variables are not wholly independent of each other. In many video games, one choice (e.g., class or weapon) impacts another (e.g., frequency of engaging the enemy or accuracy). Therefore, one spurious correlation could have many knock-on effects. To maximally ward against this effect, we elected to use the stricter α criterion of $\alpha = .01$ instead of the more common criteria of $\alpha = .05$. Additionally, we considered further bolstering the reliability of our results by applying the split-half method [40]. However, the split-half method is not feasible for the current research. Splitting the current sample in half would have resulted in a critical reduction in statistical power as the minimum sample size of 28 age groups would not have been reached [41].

C. Patterns in the Data

Correlational patterns can be found at three levels of **generalization**: across a single variable, across a variable category, and across all variables. Table I offers the necessary data for uncovering patterns on all three levels of **generalization**. The reader can discern patterns across single variables from Table I in a straight-forward manner. We discuss one example variable to illustrate how the data across single variables should be interpreted. Subsequently, we will discuss patterns across variable categories (**Action over Action, Action over Time, Score over Time, Score over Score, Time over Time**), and across all variables.

1) Patterns across Single Variables: Patterns across single variables are **a combination** of the correlations of the slope and intercept of the relevant variable. We will guide the reader through the interpretation of one single variable. Using Table
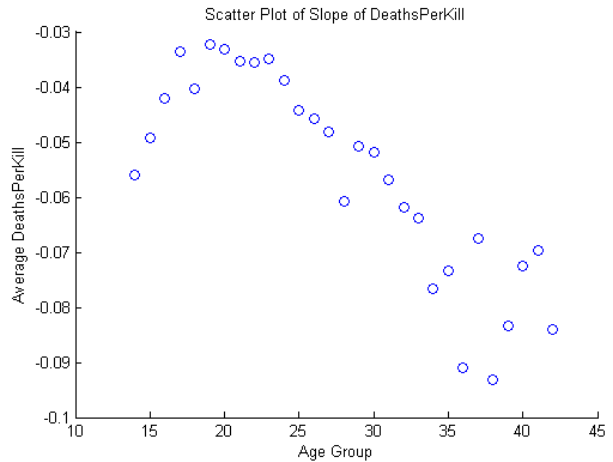

Fig. 4. The slope of DeathsPerKill shows a negative, u-shaped relationship with age, peaking around the early twenties age bracket. The DeathsPerKill values are negative for both young and old players, indicating that players of all ages decrease their DeathPerKill over time. As people age past their early twenties, they decrease their DeathsPerKill more rapidly. DeathsPerKill is a negative measure of performance.

I the reader can interpret the patterns in the remaining single variables in a similar manner.

We consider the question how kill-death ratio is influenced by age. Kill-death ratio is a central performance measure in First Person Shooters. In our analysis we have measured the inverse of kill-death ratio (DeathsPerKill), as the variable "Kills" is also a quantifier for Hits (HitsPerKill), Dogtags (DogtagsPerKill), and Savior and Avenger kills (SaviorAvengerPerKill). Figures 4 and 5 show the average slope and intercept of the variable DeathsPerKill per age group. Both plots show a u-shaped distribution with a peak around the early twenties age bracket. The overall trend is that players start out with a higher DeathsPerKill as they age (intercept), and decrease their DeathsPerKill more rapidly as they age (slope). The trend is reversed for players in their middle and late teens. As kill-death ratio is the inverse of DeathsPerKill, we may conclude that players in their early twenties start out with the highest kill-death ratio and the lowest decrease of kill-death ratio over time. Players who are progressively older or younger than the early twenties age bracket have progressively lower initial kill-death ratios and progressively higher gains in kill-death ratio over time. Kill-death ratios will converge over time. In other words, with practice players compensate for the influence of age on their kill-death ratio. Considering the units on the y-axis in both figures, we see that initial (intercept) DeathsPerKill are a factor 10 higher than the increases over time (slope). Therefore, there is considerable practice time involved before the influence of age on kill-death ratio is entirely compensated for.

2) Patterns across Variable Categories: We consider the correlational patterns per variable category.

Action over Action variables describe ratios of actions. The first seven variables in Table I are measures of performance, with DeathsPerKill and HitsPerKill being inverse measures of performance. Younger players start out with a higher performance in the game in terms of Action over Action variables,
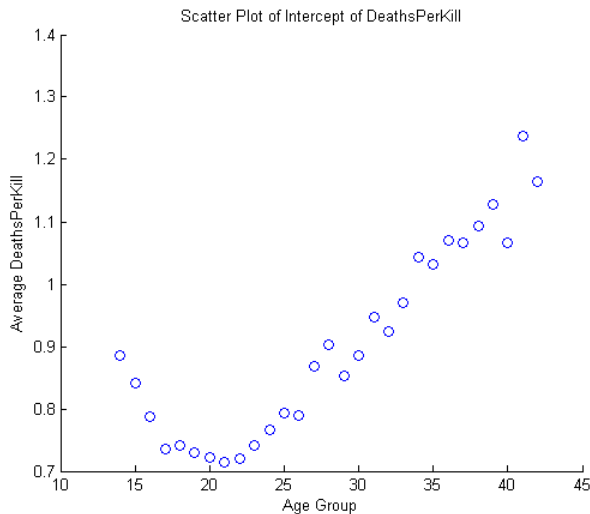
Fig. 5. The intercept of DeathsPerKill shows a positive, u-shaped relationship with age, peaking around the early twenties age bracket. As people age past their early twenties, their initial (base line) score on DeathsPerKill becomes higher. DeathsPerKill is a negative measure of performance.

with a predominant trend toward peaked correlations. Over time, older players improve their performance more quickly. The remaining six variables describe strategic and preference decisions. We have discerned no overarching patterns in the correlations of these variables with age.

Action over Time Variables describe the frequency of actions over time. The first seven variables measure game actions that require the player to kill, or assist in the killing of, an enemy. Therefore, these variables are performance-related. The remaining variables are not. Older players start out playing more slowly than younger players across all Action over Time variables. Over time, all players improve their speed. However, younger players improve faster at performance-related variables, while older players improve faster at variables that are not performance-related.

Score over Time Variables describe the frequency at which a player scores points in the game. ScorePerTotalTime is an aggregate of all types of score. UnlockScorePerTotalTime is the only score-related variable that is limited: *Battlefield 3* offers a limited number of unlockable items that offer Unlock Score. Once a player has earned all unlockable items, he cannot earn any more Unlock Score. Older players start out with lower scores over time than younger players, with a predominant trend toward peaked correlations. Correlations between the slope of the Score over Time variables and age are relatively sparse, which precludes the possibility of making overarching conclusions about the progession over time of Score over Time variables. As ScorePerTotalTime is an aggregate variable of all score variables, it does show that all players improve how quickly they score over time, with younger players improving more rapidly than older players.

Score over Score Variables describe the proportion of the scores that are earned. Initially, older players strongly focus on playing the objective and supporting their squad, while younger players focus on earning unlockable items and sup-

porting their team. Over time, score preferences level out or reverse: older players increase their proportion of unlock score and team score, while younger players focus more on the objective.

Time over Time Variables describe the proportion of time a player spends on different classes and vehicles. Older players initially prefer 'slower' classes (Support and Engineer) and vehicles (MBT and AA), while younger players prefer the remaining faster classes and vehicles. If a correlation between age and slope exists, it predominantly strengthens the existing preference of the age groups. The exception is the engineer class: EngineerTimePerTotalTime increase for all players, but does so more quickly for younger players.

3) Patterns across All Variables: Reviewing the results more generally we see that 81 of the 118 play style features correlate significantly with age (Table I). The effect sizes of the significant correlations are moderate ($r = .5$) to large ($r = .9$). Three major patterns are visible in the significant correlations: (1) Over a third of the significant correlations (mostly intercepts) is not *linear*, but *u-shaped*; (2) *speed* decreases with age; (3) *performance* decreases with age.

Linearity: 32 of the 81 play style features with a significant correlation with age peak around the age of 20. The vast majority of the peaked correlations (29 of the 32) are found among correlations between the intercept of different play style features and age. In other words, about half of the play style features exhibit a peaked correlation between the intercept and age. When a correlation is peaked ($\triangle$ in Table I) it exhibits a counter-correlational trend among early teens, peaking among either late teens or early twenties, followed by the dominant correlational trend from either early twenties or middle-to-late twenties onward (See Figures 4 and 5 for examples). The (linear) correlations are still significant and strong despite the u-shaped relationship, because relatively few age groups run counter to the dominant trend. The general theme of the correlations is that the younger a participant is, the better he performs at the game, and the faster he plays. When a relationship between age and a play style variable is linear, the highest or lowest value (depending on the direction of the correlation) is reached by the youngest age groups. However, the variables for which a u-shaped relationship exist, show that middle teens to late teens or early twenties deviate from the linear relationship that mostly exists between age and play style in (older) age brackets. Wherever a u-shaped relationship exists between age and a play style variable, most often the middle teens behave in a similar manner as the middle-to-late twenties. In these cases, the extreme value is reached by either the late teens or early twenties, depending on the variable in question. In other words, for many of the play style variables measured, there is a development as we age that changes direction once someone reaches their late teens or early twenties, i.e., one "peaks" around 20 years of age.

Speed of play decreases with age. Younger players start out playing faster ($r(i)$) than older players. Over time ($r(s)$), all players improve their speed of play, with older players improving more than younger players.

The decrease of speed of play with age can be seen in the negative correlations of all the intercepts of the Action over

Time variables. The slope feature of the Action over Time variables correlate either positively or negatively with age. The slope features that correlate negatively with age are related to variables that measure performance against another player. The slope of variables that are independent of the performance of other players, correlate positively with age. Therefore, we may conclude that all players improve their speed of play over time (slope). Older players increase their speed more quickly in regards to actions that do not depend on performance, while younger players increase their speed more quickly at actions that do depend on performance.

Performance decreases with age. Younger players start out performing better in the game in terms of kills, deaths, score, and winning ($r(i)$). Over time ($r(s)$), all players improve their performance, with no clear benefit going to either younger or older players across the board.

The decrease of performance with age can be seen in the correlations of the first seven Action over Action variables as well as all Score over Time variables. Initially (intercept) older players die more than they kill (DeathsPerKill), win less than they lose (WinsPerLoss), score less (MVP123PerRound, AceSquadPerRound, and all Score over Time variables), need more shots to kill an enemy (HitsPerKill), hit an enemy less often per shot (HitsPerShot), and land fewer headshots per shot (HeadShotsPerShot). Over time (slope), all players improve their performance. There is no consistent trend in improvement favoring either younger or older players.

D. Summary

Overall, the slope and intercept of 59 play style variables have been correlated with age for a **heterogeneous** sample of expert *Battlefield 3* player between the ages of 14 and 42. **Of the 118 possible correlation, 81 were found to be significant at** $\alpha = .01$**.** 32 of the 81 significant correlations (mostly intercepts) showed a non-linear, u-shaped relationship with age, peaking around the late teens and early twenties age brackets. As people age, they start out playing slower and worse. Over time, older players slowly make up for their speed disadvantage compared to younger players, but do not consistently make up for lower performance. Therefore, aging sets players at a disadvantage in a First Person Shooter such as Battlefield 3.

V. Discussion

In this section we discuss the pros and cons of our data analysis method, endeavor to explain the occurrence of the u-shaped curves in our data, review the generalizability of our results, and further explain the implications of our findings.

First, we would like to expand on our choice for RCA in our data analysis. More sophisticated data analysis methods such as mixed effect modeling [42] might have given us deeper insights into the data. We selected RCA due to its simplicity and transparency. The computations and reasoning behind RCA are intuitive and easy to follow. This ensures that our results can be interpreted in a straight-forward manner. Conversely, each of the results can easily be traced back to the raw data that gave rise to

it. The downside of RCA is that it does not implicitly take confounds into account such as mixed effect modeling do.

We could have added an extra step to RCA to test explicitly for confounds such as play time and gaming platform. We have chosen not to go this route because we did not expect play time and gaming platform to be strong confounds. Play time actually increases with age in our sample [10], while we would expect players to become faster and better at the game with more play time (practice). Our findings run counter to this expectation. Gaming platform is unlikely to impact the relative differences in age due to the fact that every individual on a certain platform still faces the same challenges. Therefore, the benefits of mixed effect modeling are small (more insight into confounds and interactions of variables) while the down sides are large (less insight into how the results relate to the data). Yet, for future work, we do consider mixed effect modeling a promising avenue for possibly uncovering more intricate patterns in our data set.

Secondly, 32 of the 81 significant correlations displayed u-shaped curves. The age-related developments in cognitive performance, motivation and personality (see Section II) led us to expect that the relationship between age and play style would be entirely linear. Based on an additional literature review, we suggest that the discrepancy is due to two factors: a) the age range under consideration, and b) the interaction between underlying factors. Most age-related research focuses on the effect of aging on adult development, while the human development before adulthood is split off in the field of developmental psychology. In our sample we included participants that had not yet entered adulthood, as well as those that had. We suggest that the relationship between age and play style may be different for individuals before and after the onset of adulthood. The resultant u-shaped curves are common in age-related research [43]. For example, u-shaped curves are observed in research related to executive thinking (peaking around 22 years of age) [44], and job performance (peaking around 49 years of age) [45]. Additionally, we find it plausible that different age-related factors with opposite developmental trajectories interact to create the u-shaped curves in our findings. For instance, experience and expertise develop with time, and are expected to increase with age. In contrast to this additional result we note that the cognitive benefits of youthfulness decrease with age (see Section II). The combined effect of such opposite trends would most likely lead to a u-shaped performance curve. Applied to our findings, we would like to suggest that the prevalence of u-shaped curves in initial performance and speed (intercepts) are due to such an interaction effect. We would like to suggest that future research into the relationship between age and play style will benefit from both linear and quadratic (u-shaped) modeling.

Thirdly, we would like to argue that the overall themes in the results of our research are likely to generalize to many players of other games. There are two counterarguments to this standpoint. The first counterargument is that our research suffered from an expert player bias. However, the expert player

bias was off-set by the fact that our sample was **heterogenous** in terms of age, play style, and personality. Additionally, expert players are by definition more likely to have overcome any extraneous effects on their play style, such as that of aging. Therefore, the fact that we have found a strong relationship between age and play style development *despite* our sample bias toward expert players strengthens the likelihood that the same relationship exists in the general populace. The second counterargument is that our research does not generalize to all games because only one game (*Battlefield 3*) was included. Considering the wide variety of video games in existence, we agree that our results cannot be generalized to all games. However, we do posit that our results generalize to many major commercial video game titles. The game play of *Battlefield 3* is based on two elements that are central to a wide range of commercial video games, namely action and strategic thinking. The themes in our results revolve around speed of play and performance. Both themes are pivotal within the action game genre. Additionally, Thompson et al. [46] found similar results in a sample of 3,305 *Starcraft 2* players between the ages of 16 and 44. They report that age correlates negatively with speed and performance in their sample. Speed and performance peak around 24 years of age. We hypothesize that peak performance occurs at a later age in *Starcraft 2* than in *Battlefield 3* due to a greater strategic component in *Starcraft 2*. Thompson et al. suggest older players compensate for their lack in response times through the use of game mechanics that reduce cognitive load. In *Battlefield 3* such game mechanics are not as apparent, but might play a role in how class and vehicle preferences develop over time. Older players do seem to prefer classes and vehicles that emphasize a slower play style. The research by Thompson et al. does not explore play style development over time. Still, we do consider their work to support the generalizability of our results to other game genres.

Fourthly, we believe that our findings offer valuable implications for both game developers and game researcher. Our findings provide empirical support for the intuition that aging goes hand in hand with a reduction in speed and performance in an FPS game. Additionally, the trend peaks around the age of 20, and sports high effect sizes. Game developers **might be able to** use the insights into the effect of aging on play style to adapt their games to appeal to a wider range of age groups or to deduce age data from play style data for marketing research. Our research shows that older players **are more likely to** gravitate toward a slower and less performance-oriented play style. With this knowledge in hand, game developers **may be able to** increase the size of the audience of their game (and thus the resulting revenues) by allowing players choices in the game that will satisfy both the younger and the older generations. **Researchers might be able to capitalize on these insights by controlling for age in future experiments, and expanding the exploration of the relationship between age and play style.**

VI. Conclusion

In this paper we analyzed data from a **heterogeneous** sample of 10,416 *Battlefield 3* players to answer the question

"How does a player's age relate to his play style?". We found that age relates significantly ($\alpha = .01$) and strongly ($.5 < r < .9$) to both initial play style and play style development over time. Three major trends were observed in the correlations: (1) Most play style features that correlate significantly with age, display a purely linear relationship. However, 32 play style features display a u-shaped relationship with age, where peak performance is reached by players in their late teens or early twenties. Peaked correlations were especially prevalent when relating age to initial play style (intercept). (2) Speed of play decreases with age. Over time, all players increase their speed of play, with *older* players showing the greatest gains. (3) Performance decreases with age. Over time, all players increase their performance, with no consistent benefit going toward either younger or older players. Overall, the speed and performance of the player peaks around the age of 20, and declines with age. Practice only compensates partly for the disadvantages of age by mitigating the difference in speed of play between the younger and older players.

Appendix
Spearman Correlations

Table II displays the Spearman's correlation between age and each of the play style variables. At $\alpha = .01$ there are nearly the same amount of significant correlations using Spearman's method (76) as there are using Pearson's method (81), with 7 variables only showing either a significant Pearson or Spearman correlation. The difference in effect sizes (r and ρ) is less than .1 for all 74 play styles that correlate significantly according to both the Pearson and the Spearman correlational test.

Acknowledgment

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TABLE II
AGE TO PLAY STYLE CORRELATIONS (SPEARMAN): EFFECT SIZES (ρ) ARE DISPLAYED FOR THE SLOPE (s) AND INTERCEPT (i) OF PLAY STYLE VARIABLES THAT CORRELATE SIGNIFICANTLY WITH AGE AT $\alpha = 0.01$.

Play Style Variable	Longitudinal	
	$\rho(s)$	$\rho(i)$
Action over Action Variables, range [-Inf, Inf]		
DeathsPerKill	-.84	.87
WinsPerLoss		-.74
MVP123PerRound	.53	-.84
AceSquadPerRound	.60	-.52
HitsPerKill		.66
HitsPerShot		-.84
HeadShotsPerShot		-.86
DogTagsPerKill		-.98
SaviorAvengerPerKill	.90	
GrenadeHitsPerShot		-.81
GrenadeKillsPerShot	-.57	-.74
MComDefenseKillsPerMComDestroyed		.75
FlagDefenseKillsPerFlagCapture		-.75
Action over Time Variables, range [0, Inf]		
VehicleDestroyedPerTotalTime	-.63	-.84
VehicleDestroyAssistsPerTotalTime		-.74
KillsPerTotalTime		-.95
KillAssistsPerTotalTime	—	—
NemesisKillsPerTotalTime	-.96	-.96
SaviorAvengerKillsPerTotalTime	-.55	-.98
DogTagsPerTotalTime		-.98
DeathsPerTotalTime	.73	-.83
ShotsPerTotalTime	.62	-.94
GrenadeShotsPerTotalTime	.86	
SuppressionPerTotalTime	.54	-.96
ResuppliesPerSupportTime		
RevivesPerAssaultTime	.80	-.98
RepairsPerEngineerTime		-.88
RadioBeaconSpawnsPerReconTime	.69	
Score over Time Variables, range [0, Inf]		
ScorePerTotalTime	-.70	-.92
UnlockScorePerTotalTime	.70	-.99
ObjectiveScorePerTotalTime		
TeamScorePerTotalTime	.77	-.92
SquadScorePerTotalTime		-.87
SupportScorePerSupportTime		-.94
AssaultScorePerAssaultTime		-.97
EngineerScorePerEngineerTime		-.96
ReconScorePerReconTime		-.95
VehicleScorePerVehicleTime		-.47
VehicleMBTScorePerVehicleMBTTime		-.82
VehicleAAScorePerVehicleAATime		-.92
VehicleSHScorePerVehicleSHTime		-.91
VehicleIFVScorePerVehicleIFVTime		-.80
VehicleAHScorePerVehicleAHTime	-.53	-.89
VehicleJetScorePerVehicleJetTime		-.54
Score over Score Variables, range [0,1]		
UnlockScorePerScore	.54	-.88
ObjectiveScorePerScore	-.91	.92
TeamScorePerScore	.95	-.58
SquadScorePerScore		.88
Time over Time Variables, range [0,1]		
SupportTimePerTotalTime		.94
AssaultTimePerTotalTime	-.64	-.60
ReconTimePerTotalTime		-.83
EngineerTimePerTotalTime	-.91	.97
VehicleTimePerTotalTime	-.54	-.68
VehicleMBTTimePerTotalTime		.78
VehicleAHTimePerTotalTime	-.49	
VehicleAATimePerTotalTime		.68
VehicleJetTimePerTotalTime	-.80	-.83
VehicleSHTimePerTotalTime		
VehicleIFVTimePerTotalTime	.58	

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