# Age-Based Preferences and Player Experience: A Crowdsourced Cross-sectional Study

**Max V. Birk[1], Maximillian A. Friehs[2], & Regan L. Mandryk[1]**
[1]University of Saskatchewan
Saskatoon, SK, Canada
{firstname.lastname}@usask.ca
[2]University of Trier
Trier, Germany
s1mafrie@uni-trier.de

## ABSTRACT
We tend to treat the 18-55 demographic of gamers as a monolithic and homogenous group, even though the older ones witnessed the entire rise of the videogame and the younger ones were born into a world with MMORPGs. We present a cross-sectional study of 2747 crowdsourced players aged 18-55 and conduct linear regressions of age on several measures of play habits, preferences, and play experiences. Our results show a consistent pattern that with increasing age, preferences, play motive, play style, identification as a gamer, and player experience shift away from a focus on performance and towards a focus on completion, choice, and enjoyment. We situate our results in developmental psychology, which suggests that as we age, we exhibit an increased focus on goals that prioritize emotional regulation and relationships and less on the acquisitions of new skills. Our work provides new insights into the large and core demographic of gamers.

### Author Keywords
Age; player experience, motivations; player styles.

### ACM Classification Keywords
K.8.0 [Personal Computing]: General - Games.

## INTRODUCTION
When asked to imagine a 'gamer', stereotypes suggest that we should visualize a teenage nerd playing alone; however, market research suggests otherwise. The 2016 Essential Facts report of the US-based Entertainment Software Association (ESA) states the average age of game players is 35; furthermore, only 27% of game players are under 18 years old; 29% are 18-35, 18% are 36-49, and 26% are 50 or older [22]. There are developers who design for the particular needs of the very young demographic (e.g., Sesame Street Games; Sesame Workshop) and there are also games targeted at the growing demographic of older adult gamers (e.g., Bingo Blingo; joju games)). A recent report by the Nielsen Norman Group notes that mobile game penetration has been strongest among these same young Millennials and older consumers [65]. Similarly, there are many researchers who study play motivations and experiences specifically of children (e.g., [23]) or older adults (e.g., [27,61]), but developers, researchers and marketing experts tend to treat the range in between as a monolithic and homogenous group [12,21,29,31,52].

This is true in other media as well; for example, Nielsen ratings – the primary ratings system for television– use 18-49 year olds as a target demographic because although they watch less television overall, they drive trends in purchasing [47]. In some ways, 18-55 year-olds can be considered as a homogenous group – they are out of public school and not yet into retirement; they are classified as adults and have all of the privileges (e.g., driving, smoking, drinking alcohol) and responsibilities (e.g., voting, being subject to incarceration) that comes with adulthood; and they are into a period of child rearing and child bearing if they choose that path.

Although there is homogeneity in 18-55 year-olds, there are also differences. In the year that current 55 year-olds were born (1962), the Cuban Missile Crisis took place, the Beatles released their first single, and the FCC first authorized the television remote control. In contrast, in the year that current 18-year olds were born (1999), the impeachment trial and acquittal of Bill Clinton took place, Eminem released his first major album, and the TV series *Survivor* aired before most of them saw their first birthdays. In terms of digital games, 1962 was the year that *Spacewar!* was developed by Steve Russell, and the world was still 15 years away from the North America Release of the Atari. In contrast, 1999 was the year that Everquest (a classic Massively-Multiplayer Online Role-Playing Game: MMORPG) was released, not to mention the *eighth* installment in the Final Fantasy series.

There are clearly vast differences in the historical, cultural, technological, and game experiences of an 18-55 year-old demographic, yet we tend to treat them as a single group in games user research. Researchers have little understanding of how age differentiates the play experiences of this core demographic that comprises the largest proportion of current game players. Without an understanding of the habits, preferences, and experiences of 18-55 year olds, researchers cannot understand how gamers transition from young adults into older players, designers cannot effectively optimize game design for a portion of this group (e.g., new parents), and we risk making false assumptions based on misguided biases.


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To better situate our understanding of play experience across this 18-55 year-old demographic, we conducted an analysis using 11 different studies with data from 3041 participants. Each study had a similar structure, recruitment methods, and context. More importantly, in each study, the same player demographic variables and the same self-reported player experience measures were collected.

Our results show a clear trend away from performance-related preferences and experiences toward completion-related ones with increasing age. As age increases, there is:

- An increasing preference for casual and puzzle games and a declining preference for performance-related games.
- A decline in performance as a motive to play.
- An increase in completion-focused player styles like achiever, mastermind, and seeker, and a decline in performance-focused player styles like conqueror, survivor, and daredevil.
- A decline in the identification as a 'gamer'.
- An increase in enjoyment, effort, and tension and greater satisfaction of autonomy, relatedness, and presence.
- A decline in competence (which normally co-varies with other experiential factors), which is partially explained by an accompanying decline in experienced intuitive control.

We further unpack this effect of declining competence, showing that its importance in predicting enjoyment, relative to autonomy and relatedness, declines significantly with age, and also that it takes less experienced competence to translate into similar enjoyment with increasing age.

The pattern that emerges suggests a shift of individual preferences over age away from performance and toward completion and an appreciation of choice and experience. Although most of the known results in games research are generated using data from this core demographic of 18-55 year-old gamers, treating this monolithic group as homogenous – simply because they all live in the range between children and older adults – is naïve. Over this age range, our cognitive and emotional abilities change, and we exhibit an increased focus on goals that prioritize emotional stability and relationships and less on the acquisitions of new skills. In this paper, we characterize the effects of these changes on what drives us to play games, and how we experience them.

## RELATED WORK

To understand how play experience might be affected by age, we provide a background on theories and measures of player experience and on player typologies. We describe the relationship between age and motivation, and present findings from research on video games in different age groups.

### Play Experience and Motivation

Play experience has been investigated using different theories and techniques, e.g., flow [63], engagement [15], and physiological measures [38]. The shared goal between theories and practical approaches is to understand what a player experiences under varying circumstances.

Self-Determination Theory (SDT) [54], a general theory of motivation, has been applied to games [53] and has shown a theoretically-grounded connection between in-game experiences and the resulting motivation to play [53]. SDT proposes that players are intrinsically motivated to play when three needs are satisfied: Competence – experiencing mastery over a challenge; Autonomy – engaging in a game under one's own volition; and Relatedness – experiencing meaningful relations to other players or in-game objects. The satisfaction of those three needs is commonly measured using the Player Experience of Need Satisfaction scale (PENS) [53]. SDT has been used to investigate the role of need satisfaction in different game styles, e.g., exergames [46], or serious games [67]. Other research has investigated how need satisfaction derived from different game-elements – e.g., avatar customization [12], game narratives [7], or game difficulty [4] – contributes to the intrinsic enjoyment of playing.

Enjoying a task because of the task itself and not because of a separable outcome, is the definition of intrinsic motivation [51]. Intrinsic motivation is crucial to games because it is predictive of the time invested in playing [12], the enjoyment experienced as a result of playing [53], and the effort people are willing to invest into a game [53]. Intrinsic motivation has also been shown to be predictive of purchase intentions [32], making the concept relevant for the games industry.

### *Individual Differences and Play Preferences*

To understand and predict how players feel about a game, research has considered differences in play experience itself [35], e.g., the difference between playing a world builder and playing a first-person shooter (FPS), and individual differences [44,69], e.g., whether a player enjoys competing against another player or prefers to explore a world.

Player typologies provide a categorization of differences between a player's play style, and their genre preferences. For example, Bartle's [8] player typology suggests that players can be divided into achievers, killers, explorers, and socializers. The BrainHex model [44] integrates and extends Bartle's model by proposing seven different player types: *Conquerors* are challenge focused; *Daredevils* seek thrill and risk; *Survivors* enjoy escape and terrifying scenes. *Masterminds* enjoy strategizing and puzzles; *Seekers* are discovery and exploration focused; *Achievers* aim for completion; and *Socializers* thrive most during social-interaction.

Taking a data driven approach, Yee [68] identified achievement, immersion, and social, as three components of player motivation in World of Warcraft (Blizzard, 2004). The model was recently extended to have a more nuanced and generalizable categorization of players by revamping the old categories and adding the new categories of action, mastery, and creativity to the existing model [69].

De Grove et al. [31] suggest a theory-driven approach building on Social Cognitive Theory (SCT) [6]. SCT states that behaviour is motived by processing the implication of an action, e.g., evaluating the benefits of playing games. Based on SCT, three types of expected outcomes when playing are suggested: game-internal, i.e., *performance, agency, narrative, sociability,* game-external, i.e., *pastime, escapism*, and normative outcomes, i.e., *moral self-reflection*. The authors also include *habit* to account for less conscious behaviour.

What we like to play and how we like to play contribute to the quality of our play experiences. But beyond individual differences of play style, research suggests that play experience itself differs based on our age.

### Theories of Age and Motivation

Because of the duration of longitudinal studies – i.e., studies that observe the same pool of people over time – understanding how age affects motivation and experience is a difficult topic to study. This is compounded in the domain of digital experience by the additional difficulty that events in different decades affect the beliefs and experiences of the people who live through them, e.g., people who were born pre-mobile phones have a unique relationship to communication technologies [26]. Therefore, researchers rely on theoretical models, often evaluated using cross-sectional studies – i.e., studies that look at different slices of a larger demographic group at a single point in time – to understand age-related differences in experience.

For example, one theoretical model, Socio-emotional Selectivity theory (SES) [16], explains why people tend to focus on emotional regulation goals and relatedness as they age, rather than the acquisition of a new skill. SES Theory suggests two distinct motives: those related to the regulation of emotions and those related to the acquisition of knowledge, and that our motive for knowledge declines and our motive for emotional stability increases as we age.

In line with SES, Self-Determination Theory [50] shows that older adults derive more pleasure from intrinsically-motivating work compared to younger adults, whereas younger adults are more prone to be motivated by extrinsically-motivating stimuli, such as rewards [36,37,66]. Over time, people start to gain intrinsic motivation by integrating extrinsically-motivating stimuli into their self-view, which implies that older people will find a task that was once only extrinsically motivating to be intrinsically motivating and enjoyable.

In sum, how motivated we are to engage in an activity and how we experience that activity, changes over the lifespan.

### Digital Game Experience and Age

Historic events, present technology, or the zeitgeist of a period in time affect preferences and experiences [25,49]. Therefore, to understand play experience of different age groups, e.g., children [23], or older adults [27], we need to understand the context in which they grew up.

Ferguson and Olson [23], for example, investigated the motivations for children's game play and found three distinct categories: fun/challenge, social/relatedness and catharsis/autonomy, corresponding to the three basic needs described in Self-Determination Theory [54]. However, these motivations can change with age: fantasy motivations are particularly strong in younger children [28], whereas competition and challenge-related motives are stronger in older children and adolescents [62]. In the context of games, Scharkow et al. [57] showed that young people generally sought more gratification from playing; this is in line with the aforementioned results that younger adults are more motivated by external stimuli, such as rewards [36,37,66].

There is a large body of work on the experience of older adults with digital technologies. For example, older adults tend to underestimate their knowledge and competence with computers [40] and report less self-efficacy and media competence in general [1,55]. In terms of performance in computer-related tasks, senior adults show declines due to slower processing speeds and an over-all decline in cognitive functions [19,64]. However, these declines can be alleviated by experience with technology, as experience can either preserve the original skill or can help to develop compensatory skills. Selection-Optimization-Compensation (SOC) theory [5] describes the successful aging process and how aging adults can minimize their losses while maximizing their gains. In line with SOC, video games have been shown to delay physical [27] and cognitive decline [2] for seniors.

In addition to performance differences, there are differences in genre preference with age: older adults tend to prefer more casual games [58]. De Shutter and Vanden Abeele [59] showed that seniors use games to interact with their loved ones; similarly, Quandt et al. [48] used interviews among seniors to show that they have a strong interest in the social aspect of gaming. These results are in line with socio-emotional theory, which states that relatedness and emotional contact become more important as aging progresses [16].

Taken together, these theories demonstrate that digital game researchers should consideration of age-related differences. However, the focus of digital game studies on a specific demographic (e.g., children, older adults) leaves a gap in our understanding of the habits, preferences, and experiences of digital gamers in the middle of life, i.e., aged 18 to 55 years.

## METHODS

We conduct a meta-analysis of data gathered over eleven different studies. Each study had its own research intention; however, similarities in how the studies were conducted allow us to aggregate the data into a single analysis to investigate the effects of age on player-centric traits and play experience. In each study, we recruited participants using Amazon Mechanical Turk, and used the same validated scales to assess play experience, i.e., PENS, and IMI, and player-centric traits, i.e., BrainHex and DGMS. We describe how we gathered and treated the data from these studies for analysis.

### Participants

Over eleven different studies, we recruited 3041 (mean-age=32.07, SD=9.666) participants using the crowdsourcing platform, Amazon Mechanical Turk (AMT), a broker between requesters, i.e., entities who offer Human Intelligent Tasks (HIT), and workers, i.e., people who complete the HITs. For each study, we obtained ethical approval from the University of Saskatchewan's behavioural research ethics board, and participants were asked to provide informed consent prior to beginning the experiment.

### Instruments

To assess experience and player-centric traits we used well-established, validated scales – PENS, IMI, BrainHex, and DGMS – that have been used in the context of games before [4,12,30,45,53]. PENS and IMI assess a self-reported player experience in a defined state, i.e., after playing a game. While state questionnaires provide insights into a players momentary experience, BrainHex and DGMS measure a player's more time stable traits, e.g., individual play preferences or common motives to play. In combination, trait and state questionnaires allow us to understand momentary experiences through the lens of individual differences.

**PENS:** Need Satisfaction of *competence, autonomy*, and *relatedness*, as well as *presence* and *intuitive control* as experienced during play were measured using the Player Experience of Need Satisfaction Scale (PENS, [53]) Each of the constructs were measured using a Likert-scale.

**IMI:** *Interest-enjoyment* – e.g., "I enjoyed this game very much.", *effort-importance* – e.g., "I put a lot of effort into this game.", *perceived competence* – e.g., "I'm pretty skilled at this game", and *tension-pressure* – e.g., "I felt tense while playing the game.", were measured on a Likert scale with the Intrinsic Motivation Inventory (IMI, [41]). The IMI has been used in games research before [53].

**BrainHex:** We used the BrainHex questionnaire to measure the preferred style of players [44]. Although BrainHex is intended to produce a type, it can also be used to express the degree of affiliation with a particular style of play, as was done by [45]. In our dataset, we have a rating of affiliation with the following player types: *Conquerors*, *Achievers*, *Daredevils, Survivors, Masterminds*, *Seekers, Socializers*. In ten studies, constructs were measured using the procedure described by [44]; in one case, a 4-pt scale was used.

**DGMS:** In 4/11 studies (n=604), we also collected the Digital Game Motivation Scale (DGMS) [31], which describes the different motives of people to play games. Based on social cognitive theory, the instrument measures the game-external motives of *pastime* and *escapism*, the normative motive of *moral self-reaction* (i.e., the evaluation that playing games is a valuable activity), the non-conscious behavioural motive of *habit*, and the game-internal motives of *agency*, *believability*, *involvement*, and *social* on a Likert scale.

**Genre Preferences:** We asked participants to select which genre they enjoyed playing from a list of common genres and to identify clusters of genre preferences we used K-means clustering, similar to clustering and dimension reduction approaches as used by DeGrove et al. [31] and Mandryk and Birk [39]. We identified three clusters: Casual-Puzzlers – who play only casual and puzzle games; Adventurers– who enjoy action games, FPSs, adventure, (Massively Multiplayer) Role Playing Games, and strategy games; and Comprehensives – who play a broad range of games, enjoying the same games as the Casual-Puzzlers and Adventurers combined, plus platform games, and simulations. Music games, Beat 'em ups, Sport games, and Vehicle Simulations were removed from further analysis, because they did not help differentiate clusters. To compare how frequently participants played a genre, we calculated genre percentage by age group.

**Self-identification as a Gamer:** We asked all participants to rate their self-identification as a gamer on a 10-point scale. We describe how this one-item scale significantly correlates with a 60-item validated scale on gamer self-identity in [39].

### Datasets & Game Descriptions

Datasets for this study were sourced from eleven different studies. We first ensured that all experiential data, i.e., IMI and PENS, was collected after play sessions of a minimum length of 1 min, and a maximum length of 5 min. In the case of repeated-measure study designs that exposed one participant to the same game multiple times, we averaged the experiential constructs for that study. In one study, we induced a state of social exclusion in half of the participants; however, only participants who were not exposed to social exclusion were included in the dataset used in this study.

**Instrument Scaling:** In 9/11 studies, the measures were collected on a 5-pt Likert scale. In two studies, the data were collected on a 7-point scale. We used standardized scores to address this issue (discussed in the next section).

### Data Processing & Outlier Removal

Participants were excluded from further analysis based on the following criteria: Surveys with zero variance between items, showed ratings of ±3SD in more than 2 questionnaires, answered more than 2 attention test questions (questions in which the correct answer is given in the question text – e.g., "click expert if you are reading this") incorrectly, or spent considerably less time on 2 questionnaires (-1SD) than the rest of the sample. We did not exclude people for spending more time filling in the questionnaires. Overall, 294 participants were removed, leaving 2747 in our analysis.

Data for each scale was standardized [24] using mean and standard deviation from the original datasets (i.e., for that particular study). Standardization was done to assure comparability of data independent of the number of levels in the Likert-scale, and to better account for differences between datasets due to the game used, the context of the study, the time of year, or other possible sources of variance. Creating standard scores for each original dataset before combining the datasets for analysis assured that the relative experience for each study was kept intact; creating standard scores based on the combined dataset would have been misleading, because the resulting standard scores would have been relative to the mean of the combined dataset, and not the mean of the original dataset. For each construct, we removed outliers (+-3SD) and treated the remaining data as missing data for further analysis. Outlier were removed after participants were excluded and scores were standardized.

For player experience measures, we split the overall dataset into two datasets, based on the game used. For five of the studies, we used a Match 3 game, and combined these into one dataset (n=1332, mean age = 31.49, SD = 8.349; 42.6%

female, 0.8% missing). We decided to combine data for previous studies featuring the Match-3 game, because the experience playing Match-3 is comparable between studies and measured variance cannot be attributed to different game mechanics. To further increase generalizability, we compared the Match-3 data with combined measures of the other casual games used, which had more diverse game mechanics.

The other dataset (n=1415, mean age = 30.92, SD = 8.035; 42.6% female, 0.8% missing) was comprised of data from a variety of other casual games, including an infinite runner [12], a side-scroller [13], a game of mini-games [11], and a narrative-based interactive story game [14].

For both datasets combined, the majority of our sample identifies as white (65.9%), followed by Hispanic/Latino (11.5%) and Asian (8.9%). 55.9% of our sample stated a household income lower than $45,000 per year. A Bachelor's degree was the most common educational level (33%), followed by at least 1 year of collage education (22.3%), an Associate Degree (13.3), and a Master's degree or higher (9.7%).

### Analyses
All statistical analyses were performed using SPSS 24.0 (IBM, 2016). We report linear regressions, with age as the predictor of the dependent measure. Moderated and mediated regressions were performed using the Process Macro 2.16 by Hayes [33]. A moderation analysis tests the interacting effect of a third variable, i.e., the moderator, on an established relationship between a predictor variable and an outcome variable. A mediation analysis tests the mediating influence of a third variable, i.e., the mediator, on an established relationship between a predictor variable and an outcome variable. All beta values are presented as standardized beta scores.

## RESULTS
We characterize the sample, and then establish a foundation of play preference across the sample by presenting system and genre preferences. Further, we present player-centric traits and motives to give insight into what drives people of different ages to play. Finally, we present data on play experience to explore how experience changes over age.

### Characterizing the Sample
As shown in Figure 1, there was a non-normal distribution of age (Kolmogorov Smirnov: $p<.05$), skewed toward the young. Figure 1 shows a fairly even distribution of females and males, with a very slight skew towards females in the older ranges and males in the younger ranges. Finally, Figure 2 shows play frequency of the sample, revealing that the majority of players in every age group play every week or more.

### System and Genre Preferences
In line with previously shown data [22,58], system preference data in our sample shows that personal computer and mobile use is stable over the age range (PC: beta=.00049, p=.672; mobile: beta=-.002, p=.112), whereas console use significantly decreases over the age range (beta=-.012, $p<.001$, $R^2$=.748); see Figure 3. The decreased use of consoles with increasing age is not surprising, considering that consoles only became popular in the 1990s.

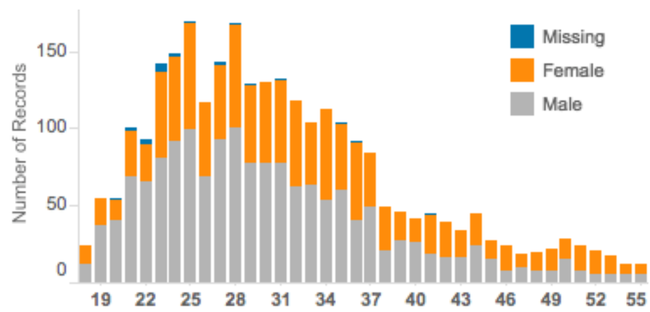


**Figure 1. Histogram of the sample colour-coded by gender.**

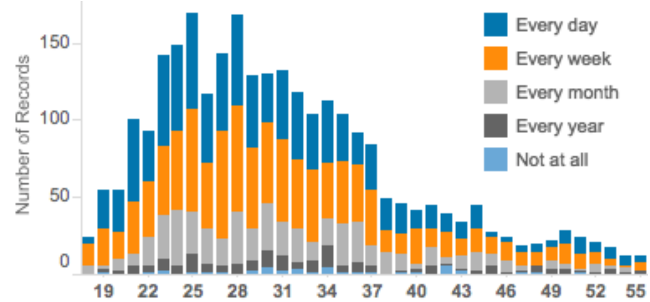


**Figure 2. Histogram of play frequency by age group, colour-coded by play frequency.**

Genre preference data shows that membership in the Comprehensive Cluster declines in popularity with increasing age (beta=-.008, $p<.001$, $R^2$=.756,). A similar decline in membership is revealed for the Adventurers Cluster (beta=-.009, $p<.001$, $R^2$=.747). The Casual-Puzzler Cluster, however, increases in membership with increasing age (beta=.0051, $p<.001$, $R^2$=.366); See Figure 3. The results suggest that with increasing age, there is an increasing interest in games that don't require an intense commitment. The increasing preference (with age) for games that are less based on reaction time, require less time commitment, and are usually easier to control can be explained in part by a lack of exposure to these types of activities in younger years, but also a lower interest in competition [69], and a focus on activities that provide more meaningful fulfillment than hedonic pleasure [16].

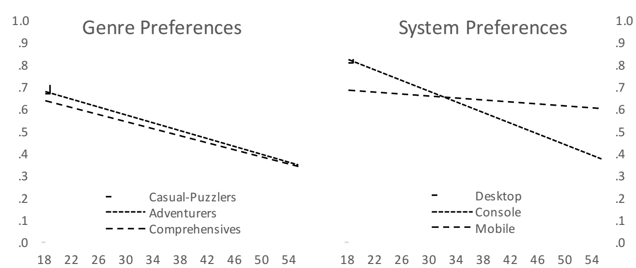


**Figure 3. Genre and system preferences by age groups.**

### Player-centric Traits and Play Motives
The BrainHex questionnaire showed that with increasing age, people self-identify more with completion-focused play styles – i.e., achiever, mastermind, and seeker, and decreasingly with performance-focused traits – i.e., conqueror, daredevil, survivor. Self-identifying as a social player – i.e., a socializer – also declines over the life-span. This result may

be partially described by the tendency of younger people to engage in social behaviour online, whereas older people may still rely on offline interaction primarily to fulfill their need to feel related to others [26].

In Figure 4, we can clearly see the increase of completion-based focused traits, and the decline of performance-focused traits. Our BrainHex results further supports that trend seen in the genre preferences that with increasing age comes an increasing preference for challenges that can be reasonably completed and not challenges that are complex, require quick reaction times, or result in overly frustrating experiences, e.g., frequently dying in a difficult game.

### *Play Motives*

Motives from the DGMS (see Table 1) show that most game-internal motivations decline with increasing age. Specifically, the narrative, performance, and sociability motives decline; whereas, agency stays stable. Habit, an indicator for non-conscious behaviour, also declines with increasing age. Moral, an indicator of the evaluation that playing games is a valuable use of time, declines with increasing age. Finally, the two game-external factors, escapism and pastime, don't change significantly with increasing age.

**Self-Identification:** Self-Identifying as a gamer decreases with increasing age (beta=-.215, $R^2$=.046, p<.001). This trend could be related to people identifying more with their career and family roles and less with their hobbies as they age [16] or because of the specific time frame we sample – we unpack this issue further in the general discussion.

## Experience Data

Self-reported experience included need satisfaction during game play, and intrinsic motivation, operationalized as experienced enjoyment, effort, tension, and competence as a result of playing a Match 3 game or one of the other games.

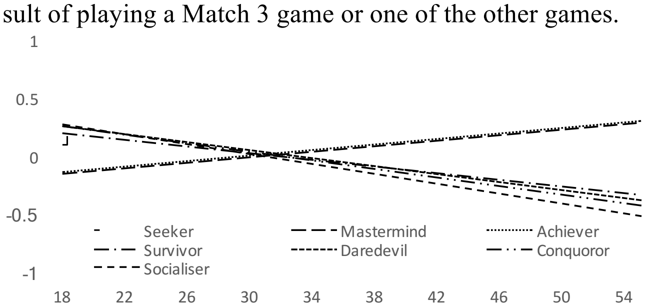


**Figure 4. BrainHex regression lines by age group.**

| BrainHex | beta | R-sq | p |
|---|---|---|---|
| Seeker | 0.007 | 0.03 | 0.003 |
| Mastermind | 0.012 | 0.011 | <.001 |
| Achiever | 0.012 | 0.012 | <.001 |
| Survivor | -0.014 | 0.013 | <.001 |
| Daredevil | -0.017 | 0.02 | <.001 |
| Conquoror | -0.018 | 0.022 | <.001 |
| Socialiser | -0.021 | 0.028 | <.001 |

| DGMS | beta | R-sq | p |
|---|---|---|---|
| Habit | -0.010 | 0.007 | 0.040 |
| Moral | -0.018 | 0.021 | <.001 |
| Agency | -0.008 | 0.004 | 0.139 |
| Narrative | -0.016 | 0.016 | 0.002 |
| Escapism | 0.001 | 0.000 | 0.866 |
| Pastime | -0.007 | 0.004 | 0.145 |
| Performance | -0.015 | 0.017 | 0.001 |
| Social | -0.020 | 0.027 | <.001 |

**Table 1. Beta, R2, and p-value for BrainHex and DGMS. Significant results are displayed with a grey background.**

### *Player Experience of Need Satisfaction*

Figure 5 shows need satisfaction for the Match 3 dataset and also for all other games combined; we find that experienced need satisfaction as a result of play increased for autonomy, relatedness, and presence with increased age. The experience of intuitive control, however, decreases with increasing age; see Table 2. It is not surprising that controls are experienced as being more intuitive for younger people, considering the age at which people in our sample were introduced to devices like mice, keyboards, and game controllers, and are thus likely to have internalized common control schemas.

Our data show that experienced satisfaction of competence does not change with age. The Match 3 game is rather simple, and outcome is partially based on the luck of the falling colours. The other games were rather simple and also not particularly challenging. Therefore, it is not surprising that competence shows only a small and statistically insignificant decrease with increasing age.

### *Intrinsic Motivation Inventory*

Figure 5 shows data from the IMI for the Match 3 dataset and also for all other games combined. For both datasets, we see that Interest-Enjoyment, Effort and Tension-Pressure increase with increasing age for both datasets.

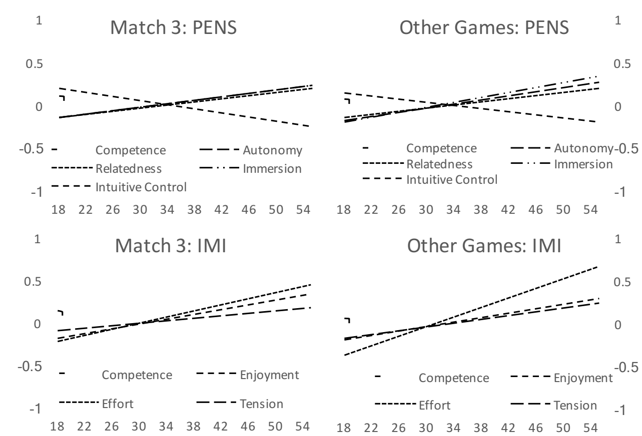


**Figure 5. PENS and IMI regression lines for Match 3 and all other games combined over age.**

| | Match 3 | | | Other Games | | |
|---|---|---|---|---|---|---|
| | beta | R-sq | p | beta | R-sq | p |
| | PENS | | | | | |
| Competence | -0.005 | 0.000 | 0.130 | -0.004 | 0.000 | 0.340 |
| Autonomy | 0.010 | 0.010 | 0.000 | 0.012 | 0.010 | < .001 |
| Relatedness | 0.009 | 0.010 | 0.000 | 0.009 | 0.010 | 0.010 |
| Presence | 0.010 | 0.010 | 0.000 | 0.014 | 0.010 | < .001 |
| Intuitive Control | -0.012 | 0.010 | < .001 | -0.009 | 0.010 | 0.010 |
| | IMI | | | | | |
| Interest-Enjoyment | 0.014 | 0.014 | < .001 | 0.013 | 0.010 | < .001 |
| Effort-Importance | -0.014 | 0.020 | < .001 | -0.003 | 0.060 | < .001 |
| Competence | 0.018 | 0.010 | < .001 | 0.028 | 0.000 | 0.420 |
| Tension | 0.007 | 0.000 | 0.040 | 0.011 | 0.010 | 0.010 |

**Table 2. Experience Data (PENS, IMI) split by Match 3 and other games.**

With increasing age, players invested more effort into the gameplay, and also derived greater enjoyment from it. They also experienced a trend of increasing experienced tension.

In the case of IMI data, perceived competence decreases in both datasets, but only significantly for the Match 3 data; see Table 2. Experienced competence decreases with increasing age; this is the trend in all measures of competence (see Figure 5), but is significant for Match 3 games and the IMI. We further unpack the results related to competence.

### *Unpacking Competence*

The results related to declining competence raise three questions: the difference in the results for the PENS and IMI scales, the mediating influence of intuitive control on competence, and the question of how competence can decline with increasing age, but enjoyment can increase.

*Why were Results Different for Competence in PENS and IMI?* Although competence declined with increasing age in all cases, it was only significant for IMI in the Match 3 dataset. As both PENS and IMI measure perceived competence, why do the results differ? To address this, we considered the individual items in the questionnaires. The IMI has five items that all center around the player's perceived competence, using terms like "competence", "performance", being "good at", and "skill" (with one reverse-coded item), whereas PENS has three items that touch on the player feeling "competent", "capable and effective", and that their "ability to play the game is well matched with the game's challenge". This last item in particular assesses a more complex aspect of perceived competence in that it requires an assessment of what the game offered and how well the player was equipped to deal with the challenge offered. This difference in the items in the PENS version of competence should be reflected in the internal consistency of the scale relative to the IMI. We checked in the three largest studies in our dataset and found that Cronbach's alpha was always higher for IMI Competence than for PENS Competence (N=488: $\alpha_I$=.88, $\alpha_P$=.79; N=174: $\alpha_I$=.85, $\alpha_P$=.78; N=99: $\alpha_I$=.86, $\alpha_P$=.64). Furthermore, the PENS alpha fell below the established threshold of 0.8 for the reliability of a questionnaire [24]. Thus is it likely that IMI gives the more reliable and consistent measure of Competence. The subsequent analyses thus all use experienced competence as measured by the IMI.

*Does Intuitive Control Mediate the Effect of Age on Competence*? When Ryan et al. [53] introduced intuitive control to PENS, they described the experience of intuitive control as a potential antecedent of competence. To determine whether the decline in experienced competence over age can be explained by the decline in the experience of intuitive control, we conducted a mediation regression model [33] of age on competence with intuitive control as a mediator. We used both datasets combined. As shown in Figure 6, there is a total negative effect of age on competence, which remained a significant direct effect even after intuitive control was included as a mediator in the model, although the beta value dropped from -.008 to -.004. The bootstrapped confidence intervals for intuitive control as a mediator did not include zero [33], suggesting a partial mediation. That is, some of the variance in declining competence can be explained by declining intuitive control, but not all of it. Hence, age is the explaining factor for the decline in perceived competence, but the perceived intuitiveness of the controls also affect competence, i.e., unintuitive controls further lower perceived competence.

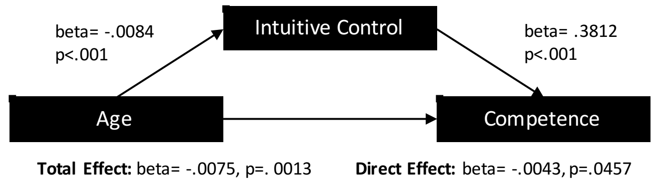


**Figure 6. Mediation graph for Age on Competence, mediated by Intuitive Control – beta- and p-values are included.**

*How can Experienced Competence Decline over Age while Enjoyment Increases?* In most player experience research, experienced competence is either a predictor of enjoyment (e.g., [53]) or at least varies in tandem with enjoyment (e.g., [43]). This is supported by Self-Determination Theory, which suggests that the satisfaction of competence leads to intrinsic motivation [54]. In our sample, competence declines over age, whereas enjoyment increases. These results suggest that as people age from 18 to 55, the satisfaction of competence becomes a less important predictor of enjoyment (relative to, for example relatedness and autonomy) and/or that it takes less satisfaction of competence to result in the same amount of enjoyment. We explored these two options.

The first explanation (importance) would be reflected in significantly declining beta values of competence in a regression of competence, autonomy, and relatedness on enjoyment for increasing ages. As such, we conducted a linear regression with competence, autonomy, and relatedness as three predictors of enjoyment, separately for each age on our combined dataset. Figure 7 shows the standardized beta values over age for these 38 regressions, and clearly shows that the weight placed on competence decreases over age (as does relatedness), whereas autonomy increases over age. This decrease in the importance of competence is significant (p=.045). It is important that the three predictor terms were entered into a single model as this result demonstrates that the relative weight of competence, in the presence of autonomy and relatedness, decreases in terms of the prediction of enjoyment. As such, we can assume that the relative importance of competence in predicting enjoyment decreases.

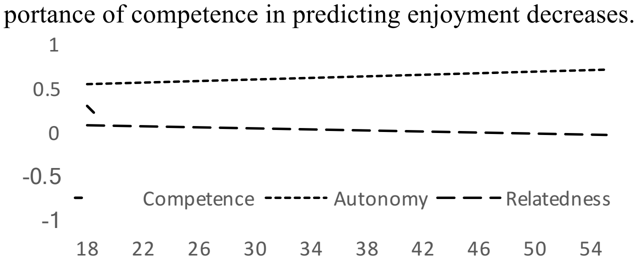


**Figure 7. Regression lines for the beta-values from a multiple regression of Competence, Autonomy, and Relatedness on Enjoyment over age.**

The second explanation (that it takes less satisfaction of competence to yield enjoyment) would be revealed through a significant moderation. We conducted a moderated regression [33] with age as a predictor of enjoyment, moderated by competence. Results reveal that both age ($p<.001$) and competence ($p<.001$) were significant predictors of enjoyment and that the moderation was also significant ($p<.05$), showing that there is an interaction between age and competence in predicting enjoyment. The moderation results revealed that although competence predicted enjoyment significantly for each age range, the prediction became shallower (i.e., beta value decreased) with increasing age ($\beta_{younger}$=.453; $\beta_{middle}$=.416; $\beta_{older}$=.380) – that is, it takes less satisfaction of competence to yield the same enjoyment with increasing age.

## DISCUSSION

In this section, we summarize our results, explain our findings through the lens of game preferences, motives and play styles, and through the lens of prior experience. Further, we distinguish the effects of prior experience from the effects of aging. Finally, we present limitations and future work.

### Summary of Results

Our results show a clear trend over the range of the 18 to 55 year-old demographic away from performance-related preferences toward completion-related preferences. We show that as age increases, there is an increasing preference for casual games and puzzle games and a decreasing preference for performance-related games. This trend is also reflected in play style and motives to play – with increasing age, performance as a motive to play decreases, completion-focused player styles like achiever, mastermind, and achiever increase, and performance-focused player styles like conqueror, survivor, and daredevil decline. Both the social motive (drive to play) and the socializer play style decline significantly with age. Furthermore, the identification as a 'gamer' declines with age.

Experience data also aligns with this trend; we reveal that with increasing age, people derive greater experienced enjoyment, effort, and tension from play. The increase in game enjoyment with age is also reflected in the increased satisfaction of autonomy, relatedness, and presence. However, competence (which generally co-varies with the other IMI factors) does not increase, and in some cases significantly declines with increasing age. Furthermore, this decrease in competence is partially explained by an accompanying decline in the experience of intuitive controls – both competence and control are related to the player's experience of their own performance during play. We further unpack this effect of declining competence, showing first that its importance in predicting enjoyment (relative to autonomy and relatedness) declines significantly over age, and that less satisfaction of competence translates into the same amount of enjoyment as age increases.

The pattern that emerges suggests a shift of individual differences and preferences over age away from performance in terms of play motive, play style, identification as a gamer, and player experience. As players shift away from performance, they shift toward completion in terms of play style and are appreciative of experience, valuing choice and experiencing more intrinsic motivation during play. These findings can be explained by existing theories of emotional, and cognitive changes over age.

### Explanation for Findings

Older age groups identify less as gamers than younger age groups – a trend that doesn't come as a surprise, considering that the older generation was in their teens when the Atari was released in 1977 and were well into careers and child-rearing years when the original Sony PlayStation was released in 1995. In contrast, the low-end of our age range were all born years after the release of the PlayStation. In addition to age, differences in exposure affect what people like, what motivates them to play, and how they experience games.

#### *Preferences, Styles, and Motives*

Scharkow et al. [57], for example, showed that younger people have a stronger preference for most game genres than older adults, with the exception of card games and simulations. On a similar note, Bilgihan et al. [9] found statistical evidence that the older generation focuses more on strategic gaming whereas the younger generation tends to affiliate more with action games. Our sample supports these findings, showing that the older generation tend to get categorized in the Casual-Puzzler cluster and less in the Adventurer and Comprehensive clusters, while the younger generation shows the opposite. Considering that puzzle and casual games often build on known concepts (e.g., a digital version of an existing card game) or use a common puzzle mechanic (e.g., Match 3), the preference of older adults might be explainable by psychological theories that suggest that with increased age, people prefer familiar tasks and experiences [3,6,16]. The classic theory of mere-exposure [71] states that we develop preferences because of mere familiarity, which increases exposure and further increases familiarity in a positive feedback loop. For example, playing cards will increase your preference for cards and likely make you play more cards. Considering that older age groups had more exposure to puzzle games than to FPS and RPG games, the familiarity principle may partially explain their preferences. These results are also in-line with research showing that highly-practiced processes stay accessible later on in life [18].

Models of personality (e.g., Big-Five [42]), models of play style [44], and player archetypes [20] have been used to understand individual differences between players. De Schutter & Malliet [60] categorized senior adults into five types of players: *time wasters* (only casual games), *freedom fighters* (free to play a game and avoid work), *compensators* (playing games as a result of a deficiency), *value seekers* (to learn a lot from games) and *ludophiles* (people who had been gamers for their whole life). Other approaches have focused on the self-ascribed motives of players to engage in play. Using a large sample of more than 239,000 players, Yee et al. [69], showed that the competition motive declines over age; based on the same data source, [69] showed that interest in playing with others declines over age, except for co-located, cooperative games played with friends.

Our results show that there is a trend over age: younger ages see themselves more as performance and competition oriented, whereas older ages show a decline for the same constructs and see themselves more as completion-focused. The relationship between completion- and performance-focused play preferences confirms and extends Yee's findings by showing that it isn't just that competitive and performance traits decline over age, but that completion traits increase.

We also show that game-internal motives for play decline over age. Older ages seem to be less interested in the high-standards and technologies that the AAA market drives. For example, sophisticated social systems (as was done in, for example, Eve Online; CCP Games, 2003), are less likely to appeal to older ages. These results seem to highlight an opportunity for game developers to create games for this demographic that have a lower social demand, stay away from a heavy narrative, and are easy to access – similar to many casual games that are already released on the market.

*Experiences*

The consistent pattern of performance versus completion related games for younger and older age groups leads to the question of how experience is affected. The casual games used in all eleven studies allow us to investigate how different age groups experience a casual game. As individual differences suggest, we can show that older people experience more need satisfaction and higher levels of enjoyment, effort, and tension, whereas competence and the intuitiveness of control decline over age groups. Our results are in line with previous results that show that competence is in part a function of being able to control the game [10,43,53]. Furthermore, there are theories that help explain our findings.

Socio-emotional selectivity (SES) theory [16] argues that people focus on emotional regulation and relatedness centric goals as they age, rather than the acquisition of a new skill. Older age groups might experience the game as more satisfying, because they have a tendency to perceive events as emotionally more positive than younger age groups. SES theory would also suggest that older adults are aware of their decline in cognitive and physical abilities, consequentially they rate themselves as less competent. Our sample only extended to age 55, however, and does not access people experiencing the more drastic age-related decrements in cognition and physical ability [56].

How much does cognitive decline over the age represented in our sample affect performance? We don't evaluate game performance in this study, but based on prior research, we know that the decline of ability is often compensated for through knowledge. For example, Horn & Cattell [34] suggested that a lack of one ability (e.g., age-related decrease of reaction time) is often compensated for in experience and knowledge (e.g., remembering the spawn time of important items on a FPS map). As a result, self-perceived performance might decline, but other mechanisms might be in place that prevent declines in actual performance over this age range.

**Digital Exposure versus Effects of Aging**

As noted previously, the digital experiences of this age range differ quite dramatically. It is not surprising that the control schemes of games are experienced as less intuitive with increasing age, as people in the older end of the age range likely remember learning to use a mouse well into their adulthood, whereas the younger end of the range never lived in a world where the mouse was not a standard input device. Our sample represents a truly interesting group in terms of their exposure to digital technologies. The older group was born the year that Spacewar! was programmed, witnessed the rise of the arcade, the invention of home gaming, personal computing, mobile phones, and the Internet – all technologies that were already present when the youngest group was born.

Throughout, we have alluded to these differences in exposure to technology as potential sources of the changes in preference and experience that we see over the age range. Research supports the prospect of exposure to technology-driving differences in the experience of it. For example, older adults report less competence and self-efficacy with technology [1,40,55], but that exposure to technology and intergenerational contact can decrease anxiety and increase perceived competence about technology use [17]. And it isn't just subjective experiences that can be offset by exposure – performance differences related to general cognitive and age-related decline in functioning have been shown to be offset by experience [19,64].

Some researchers have suggested that differences between younger adults and older adults may fade over time if controls don't change drastically because the older adults will have played games their whole lives [60]. This argument around 'digital natives' as older adults makes sense from our perspective as researchers in 2017; however, history suggests that the next 50 years will bring about technological changes that we can't even begin to imagine now. As such, there will likely be future papers written about how our young cohort, born in 1999, are disadvantaged users of technology in their older years as they were not exposed to some unimaginable future technologies until well into their adulthood.

We previously situated our results in theories that explain cognitive and emotional changes over age. Here, we have described how exposure could contribute to the source of the differences. Although it is unclear whether our results should be attributed to changes in age or differences in exposure to games and digital technology in general – and is most likely a combination of both – the likelihood of future technological development implies that this pattern will continue for future cohorts of 18-55 year olds.

**Limitations and Future Work**

Our work provides new insights on the differing preferences, motives, play styles, and experiences of people in the 18-55 year-old age bracket. Although we are careful in the use of our terminology throughout, we would like to make explicit some of the limitations of the study and the care that must be taken when interpreting the results.

First, our results demonstrate trends in aggregate. Although performance-driven motives decrease in general over age, this does not imply that a 40-year old cannot have a higher performance motive than a 20-year old player. As with all population estimates, data of the different groups is made up of overlapping distributions. The individual difference within an age bin is much larger than the differences between neighbouring bins. Although the results do reflect the general trends over the sample, we must be careful not to overgeneralize with these types of findings to stereotype or pigeonhole individual people.

Second, we present a cross-sectional sample, which allows us only to draw conclusions about differences in age bins taken from the current population. It does not, however, allow us to draw conclusions about changes over time, i.e., the lifespan, which would require longitudinal studies that investigate change in a single cohort over multiple years. This limitation makes it impossible to determine whether the results can be attributed fully to changes as a result of the aging process or whether they can also partially be attributed to changes in digital exposure in the different age ranges of our participants.

Third, the results that we present are small but significant trends. The figures show how the slopes of the lines are not generally drastic, which is to be expected as peoples' habits and preferences don't change instantly, but slowly over a range of years. Even small slopes, however, show a big difference over a range of ages as big as 18-55.

Fourth, we present results from an age range between 18 and 55 who participated in studies playing casual games, which are preferred by older age groups. Replicating the results with a different genre would be valuable.

Finally, the number of participants in each age bin is not equivalent. While our findings are well supported by prior findings and grounded in literature, it would be of interested to have equally sized age-groups to investigate more nuanced differences. Similarly, it would also be of interest to increase the age range towards young children and seniors, which are both not covered in the current study.

## CONCLUSIONS

The current core demographic of 18 to 55 year-olds is a particularly interesting group because of the diversity of their historical exposure to digital technologies in general and games in particular. The older range of this group witnessed the entire rise of the videogame – from a research prototype in an MIT lab to a world in which a game that lives on your smartphone supports the networked online play of more than 50 million daily active users [70]. The younger range were already born into a networked world of downloadable content and multiplayer coop modes. Although there are clear differences in the digital exposure of this group, we tend to treat them as a monolithic and homogenous group in games user research.

In this paper, we consider the play preferences, styles, and motives of 2747 players in this age range. Furthermore, and unique to other work in this area, we investigate differences in standard measures of play experiences that were gathered in the context of eleven similar experiments. Our results show a consistent pattern that with increasing age, preferences, play motive, play style, identification as a gamer, and player experience shift away from a focus on performance and towards a focus on completion, choice, and enjoyment. Our findings can also be explained by socio-emotional selectivity theory, which suggests that as we age, we exhibit an increased focus on goals that prioritize emotional stability and relationships and less on the acquisitions of new skills. We provide new insights into the player experience of this core demographic of gamers.

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