Age and Performance in League of Legends

Athanasios V. Kokkinakis
Computer Science Department
University of York
YO10 5GH, York, United Kingdom
avk504@york.ac.uk

Abstract

As adolescents age, their reaction times decrease while their fluid intelligence increases (the ability to solve abstract problems). Here I examine whether maturational effects are present in a popular videogame "League of Legends" by looking at individuals' Matchmaking Rating MMR (how good they are at the game) and their age (14-27). I briefly discuss similar finding of age and performance in other game genres in the literature such First Person Shooters and Strategy games. I will finally discuss the implications of these findings for game design in addition to their use in predicting healthy aging.

Introduction

In a number of sports, individuals reach their peak performance in their mid-twenties. Some of this maturational profile is driven by physical development but success in many sports also depends on executive control and reaction times which follow the same timecourse (Ericsson, 1993). This is supported by studies looking at reaction times where participants have to press a key in response to a brief stimulus appearing on a screen (Bellis, 1933; Sheppard & Vernon, 2008). It is not surprising then that aging effects would be present in modern videogames which not only require the aforementioned reaction times and executive control but also tap additional constructs such as problem solving.

Methods

The videogame company Riot provided us with a dataset of individuals' in-game stats for their videogame League of Legends. These stats included players Matchmaking Rating (MMR) which represents how good a player is at the game. More details on the specifics of the sample can be found in Kokkinakis et al., (2016). We extracted players' real age through their nicknames. In order to cross-correlate the real birthdate with their extracted one Riot also provided us with the ages used when registering an account for their game.

Results

Inactive accounts were filtered by selecting participants who had played at least 100 games. The age range examined was between 14 and 27. Players' MMR was converted to z-scores. The age group 23 was excluded from the analysis because it was both disproportionally represented in terms of population and it also had the biggest variance in terms of MMR when compared to other age groups. Psychologists at Riot informed us that this age was what appeared first when players registered which may have prompted individuals to click it so they download the game faster regardless of their actual age.

Tukey's method for outlier rejection was used to eliminate each age group MMR outliers. The final sample was n=10,967. Q-Q plots were inspected and the groups were found to be normal (the Kolmogorov-Smirnov test can be problematic in large samples) (Field, 2009). A partial correlation controlling for games played was subsequently carried out.

There was a significant correlation between MMR and age even after controlling for games played with $r=.17$, $p<.001$. Note that even though it is significant it is still a relatively small relationship.

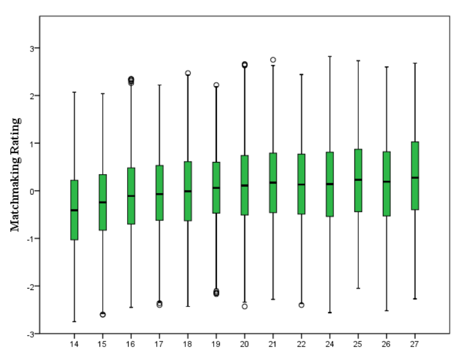

Figure 1.Average MMR per age group. Performance increases as one ages. It should be noted that different games might have different ages for peak performance.

Discussion

One can see that there is an increase in MMR and thus game performance as players reach their mid-twenties. Of course this link between age and MMR should be viewed cautiously since it does not account for individual differences or third order variables such as fluid Intelligence. Moreover, as one can see in Figure 1 the range of MMR achieved by each age group is quite big so one's age should not be viewed as an end all of performance. However, aging-maturational effects still exist.

This aging effect has been replicated in videogames of various genres such as a first person shoot (FPS), where Tekofsky and her colleagues (2015) claim that the peak age is approximately around 20 as well as Starcraft 2 where Thompson and his colleagues (2014) pinpoint peak performance at Age 24. Moreover, if we look at Liquidpedia (Retirement, n.d.), a website which records the dates professional players retired from the Starcraft II scene, we can see that players who are 24 years old are disproportionally represented in line with Thomson's and his colleagues' findings (2014).

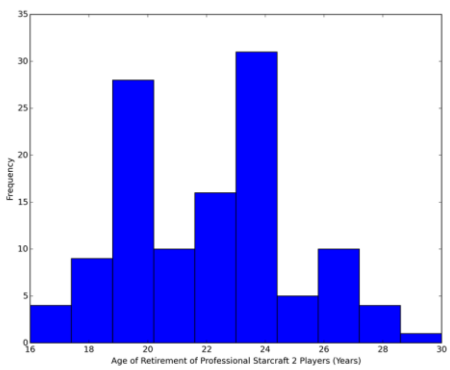

Figure 2. Age of Retirement of Professional Starcraft 2 players scraped from Liquidpedia. There is a disproportionate amount of players retiring around the age of military conscription in Korea and then at the age Thompson's et al., (2014) suggest. These data should be viewed as complimentary to other studies and should be taken with a grain of salt.

It is evident that different videogames tap different mental constructs which may account for the differences in everyone's findings. As an example FPS may rely more on fast reaction times rather than strategic thought.

If we are to interpret these findings in terms of game design, a user's Age can be used for player calibration when they play their initial placement matches which will decide their initial MMR and thus the quality of their opponents. This might help prevent a lot of unnecessary losses which may affect user experience and even user retention.

Age could also act as a good predictor in terms of skill acquisition, helping place individuals in the appropriate MMR bracket faster based on a projected trajectory of skill learning which varies according to age. On a similar vein, videogame companies could create less complex in-game characters if they are targeting a younger demographic. By less complex we mean characters with more targeted abilities that are easier to aim at the opponents. These characters will fit the playstyle of younger individuals by requiring simpler execution of their skills.

Finally, videogame scores can be used to infer players' mental abilities (for instance performance/visuospatial IQ) (Rabbitt et al., 1989). It could be possible for a health related organization to establish in-game player performance of a healthy cohort and then use that as a gold standard comparing it with at-risk populations flagging players who are acting as outliers (significant performance drop through in-game stats that does not correspond to their age group) (Thompson et al., 2013).

References

Ericsson, A.K. (1993). Peak Performance and age: An examination of peak performance in sports. In Baltes, P. B., & Baltes, M. M. (Ed.), *Successful Aging: Perspectives from the Behavioral Sciences* (pp. 164-178). Cambridge University Press.

Field, A. P. (2009). *Discovering statistics using SPSS: and sex and drugs and rock 'n' roll* (third edition). London: Sage publications.

Kokkinakis, A. V., Lin, J., Pavlas, D., & Wade, A. R. (2016). What's in a name? Ages and names predict the valence of social interactions in a massive online game. *Computers in Human Behavior*, *55*, *Part B*, 605–613. http://doi.org/10.1016/j.chb.2015.09.034

Rabbitt, P., Banerji, N., & Szymanski, A. (1989). Space fortress as an IQ test? Predictions of learning and of practised performance in a complex interactive video-game. *ActaPsychologica*,*71*(1–3),243–257. http://doi.org/10.1016/0001-6918(89)90011-5

Retirement. (n.d.). In Liquidpedia. http://goo.gl/CDWrSU

Seo, S. (2006, August 9). A Review and Comparison of Methods for Detecting Outliers in Univariate Data Sets [University of Pittsburgh ETD]. Retrieved 26 May 2016, from http://d-scholarship.pitt.edu/7948/

Sheppard, L. D., & Vernon, P. A. (2008). Intelligence and speed of information-processing: A review of 50 years of research. *Personality and Individual Differences*, *44*(3), 535–551. http://doi.org/10.1016/j.paid.2007.09.015

Tekofsky, S., Spronck, P., Goudbeek, M., Plaat, A., & van den Herik, J. (2015). Past Our Prime: A Study of Age and Play Style Development in Battlefield 3. *IEEE Transactions on Computational Intelligence and AI in Games*, *7*(3), 292–303. http://doi.org/10.1109/TCIAIG.2015.2393433

Thompson, J. J., Blair, M. R., Chen, L., & Henrey, A. J. (2013). Video Game Telemetry as a Critical Tool in the Study of Complex Skill Learning. *PLoS ONE*, *8*(9), e75129. http://doi.org/10.1371/journal.pone.0075129

Thompson, J. J., Blair, M. R., & Henrey, A. J. (2014). Over the hill at 24: persistent age-related cognitive-motor decline in reaction times in an ecologically valid video game task begins in early adulthood. *PloS One*, *9*(4), e94215. http://doi.org/10.1371/journal.pone.0094215