L33t or N00b? How Player Skill Alters the Effects of Network Latency on First Person Shooter Game Players

Shengmei Liu, Mark Claypool
sliu7,claypool@wpi.edu
Worcester Polytechnic Institute, Worcester, MA, USA

Atsuo Kuwahara, James Scovell, Jamie Sherman
atsuo.kuwahara,james.j.scovell,jamie.sherman@intel.com
Intel Corporation, Hillsboro, OR, USA

ABSTRACT

Game players generally want low network latency to maximize their chances of winning – in general, the lower the network latency, the less time between a player's action and the intended outcome. But how much network latency affects players with different levels of skill is not known. This paper presents results from a 36-person user study that evaluates the impact of network latencies on *Counter-strike: Global Offensive* (CS:GO), with skilled FPS game players divided into two groups – one group with extensive CS:GO experience and the other not. Analysis of the results shows that network latency impacts higher-skill players more than lower-skill players, with higher-skill players suffering greater score, accuracy and Quality of Experience degradations than do the lower-skill players for the same network latency.

CCS CONCEPTS

• Applied computing → Computer games; **• Human-centered computing** → *User studies.*

KEYWORDS

skill, gamer, FPS, user study, esports, lag, CS:GO

ACM Reference Format:
Shengmei Liu, Mark Claypool and Atsuo Kuwahara, James Scovell, Jamie Sherman. 2021. L33t or N00b? How Player Skill Alters the Effects of Network Latency on First Person Shooter Game Players. In *Workshop on Game Systems (GameSys '21) (GameSys '21), September 28-October 1, 2021, Istanbul, Turkey*. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3458335.3460811

1 INTRODUCTION

Computer games are one of the world's most popular forms of entertainment, with global sales increasing at an annual rate of 10% or more [24]. Because of the visibility of esports – by 2023, there are expected to be about 300 million frequent viewers of esports worldwide [10] – attention is often paid to the performance of highly-skilled players. However, lower-skilled players make up the majority of revenue for most game companies, so understanding the impact of networks and systems on players with different levels of skill and experience is important.

Network latency between a player's computer and the server managing the game state can impact the responsiveness and consistency of an online game, hurting performance and degrading quality of experience. Gamers often try to reduce network latencies, following the conventional wisdom that "faster is better." What is not known, however, is how much network latencies affect players with different levels of skill.

There have been studies on network latency and commercial games [8, 13, 26], especially latency and first-person shooter (FPS) games [2, 3, 17, 23] owing to the sensitivity of FPS games to network latency and the prevalence of FPS games in the competitive and esports scenes. Other latency and games research has studied network latency for custom games, sometimes with the focus on a particular game action [14, 16, 18, 19]. While valuable for understanding latency and games and even latency and user interaction, such studies do not compare and contrast the effects of latency based on player skill. While some research has provided indication that player skill does impact the effects of latency [4], the extent to which these results hold for full games is not known, nor have small scale studies that show skilled players may adapt to latency [1] been replicated to larger studies with more statistical power. To the best of our knowledge, there are no studies of gamers grouped by skill playing a commercial game with low-end (less than 150 milliseconds) network latency. The impact of network latency on players in different skill groups is of particular interest since it motivates both innovators to reduce network latencies and players to purchase their innovations.

This paper presents the results from a user study that measures the impact of network latency on players in two distinct skill groups. Users were screened for their skill at the FPS game *Counter-strike: Global Offensive (CS:GO)* (Valve, 2012). The initial intent had been a single group of users comprised of only experienced CS:GO players. However, with a reduced participant pool due to the COVID pandemic, we were forced to include players that were experienced with FPS games but not with CS:GO. In analyzing their performance, it was clear the groups had different CS:GO skills. This presents an opportunity to compare the effects of network latency across the two groups. All users played rounds of CS:GO with controlled amounts of network latency.

Analysis of the results shows that while the higher-skill players perform better than the lower-skill players, network latencies impact the higher-skill players more than the lower-skill players. Compared to the lower-skill players, when encountering network latency, higher-skill players suffer 50% more in accuracy and 400% more in score. Higher-skill players also notice network latency more, with their QoE degrading by twice that of lower-skill players for the same increase in network latency.

GameSys '21, September 28-October 1, 2021, Istanbul, Turkey

ACM ISBN 978-1-4503-8437-7/21/09…$15.00
https://doi.org/10.1145/3458335.3460811

The rest of this paper is organized as follows: Section 2 describes previous related work on network latency and games; Section 3 describes our methodology, including CS:GO setup and user study design and execution; Section 4 summarizes the demographics and overall user performance for our two skill groups; Section 5 analyzes the results from the user study, comparing the two skill groups; Section 6 mentions some limitations of our methods; and Section 7 summarizes our conclusions and presents possible future work.

2 RELATED WORK

Counter-strike Global Offensive's (CS:GO) (Valve, 2012) longevity in competitive gaming has motivated CS:GO use in related research. Jansz and Tanis [15] find Counter-strike players are foremost motivated by social reasons, even for gamers that are also motivated by competition and challenge. Makarov et al. [20] find ranking CS:GO players based on their team impact useful for predicting winners. While helpful to better understand CS:GO players and their interactions and performance in the game, these papers do not delve into the effects of network latency on players nor analyze user groups based on skill in CS:GO, as does the work in our paper.

For network latency and FPS games, Armitage et al. [2] estimate the network latency tolerance threshold for Quake 3 to be about 150-180 ms. Quax et al. [23] find Unreal Tournament 2003 players suffer with network latency and jitter as low as 100 ms. Amin et al [1] demonstrate player experience determines network latency sensitivity for Call of Duty, with competitive gamers more adept at compensating for impaired network conditions. For other game genres, Fritsch et al. [8] find players of the role-playing game Everquest 2 can tolerate hundreds of milliseconds of network latency. Hoßfeld et al. [13] show players of the casual game Minecraft are insensitive to network latencies of up to 1 second. Sheldon et al. [26] find some aspects of play in the real-time strategy game Warcraft 3 are not affected by up to a second of network latency. Pantel et al. [21] demonstrate players of a custom car racing game are not critically affected by delays up to 50 milliseconds, but that delays over 100 ms should be avoided. While beneficial in understanding the impact of network latency, these works do not identify nor isolate the player's skill in their assessment of network latency's impact, unlike our work.

There is some, albeit limited, work investigating the effects of latency on players with consideration to skill. Claypool [4] triage 51 users into three skill groups, have them play a target selection game with latency and show that higher skill players are resilient to performance degradations for latencies above 350 milliseconds. While useful for some interactive applications, these delays are much higher than many gamers experience, especially higher-skill players in competitive games. Amin et al. [1] query two users with different amounts of skill after playing Call of Duty with delay and infer that higher-skilled players notice even small amounts of latency but are able to compensate for it better than lower-skill players. As the authors themselves note, their sample size and objective evaluation are far too small to generalize. Dick et al. [6] separate 8 users into two teams, have them play four FPS games with network latency and jitter to study the factors that impact players, finding skill impacts score but not mean opinion score (MOS). While useful for understanding the factors that affect players, there is no comparison in performance and experience between players in different skill groups. Also, player skill is differentiated by self-report score only.

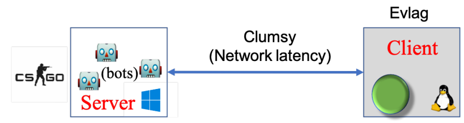


Figure 1: CS:GO computer configuration

3 METHODOLOGY

To investigate network latency on first person shooter (FPS) game players, we configured a client-server system with a competitive FPS game, added controlled amounts of network latency, recruited players for a user study, measured player performance and quality of experience, then analyzed the results from two skill groups.

Our user study was conducted in a dedicated, on-campus computer lab using a client-server architecture shown in Figure 1. The server hosted the game and was connected via high-speed LAN to the client. The client and server were Alienware PCs each with an Intel i7-4790K CPU @4 GHz with 16 GB RAM and an Intel HD 4600 graphics card. The client was equipped with a gaming mouse and high-refresh rate monitor so as to minimize local system latency. The client had a 24.5' Lenovo LCD monitor with 1920x1080 pixels at 240 Hz and a G502 laser mouse with 12k DPI, 300 IPS, and a 1 KHz polling rate. The client ran Ubuntu 20.04 LTS, with Linux kernel version 5.4 and the server ran Windows 10. Both server and client ran *Counter-strike Global Offensive (CS:GO)* (version 10.15.2020). Users were provided wired Apple earpods for audio.

The base system latency was measured with a 1000 f/s camera (a Casio EX-ZR100), setup to capture the moment a user pressed the mouse button and the resulting screen output. By manually examining the video frames, the frame time when the mouse was clicked was subtracted from the frame time the result was visible, giving the base system latency. This measurement method was done 10 times on our client, yielding an average base latency of 24.6 milliseconds, with a standard deviation of 3.4 milliseconds.

To test the effects of network latency, latency was added equally to the server uplink and downlink using Clumsy,[1] a network filtering tool based on the WinDivert library. The total round-trip network latencies experienced by the users were 25, 50, 100, and 150 milliseconds (ms). The LAN latency was less than 1 ms.

Table 1: Weapon attributes

Weapon	Mode	Fire rate	Clip	Reload	Damage	Accuracy
AK-47	Automatic	600 per min	30	2.43 s	36	21.74 m

While CS:GO matches often include team strategy, the focus of this study is on the effects of network latency on individual player tactics. As such, a death match free-for-all game mode (no teams) was chosen. Each round had open combat for the user and 20 AI-controlled bots, where everyone fought everyone and the goal was

[1] https://jagt.github.io/clumsy/

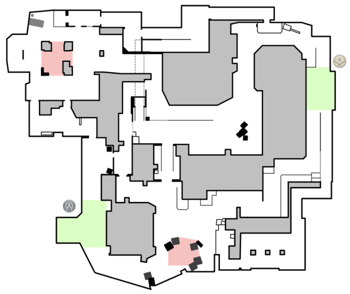


Figure 2: User study CS:GO map – Mirage

Table 2: Subjective questions per round

	Rate:	Source
Q1	The quality of the round	Stadia [9]
Q2	The responsiveness of the round	Long [19]
Q3	Your annoyance with the unresponsiveness	GEQ [22]
Q4	The inconsistency of the round	Custom
Q5	Your annoyance with the inconsistency	GEQ [22]
Q6	How capable and effective you felt	PENS [25]
Q7	How fun the round was	GEQ [22]
Q8	Your frustration in the round	iGEQ [22]
Q9	How much your performance was due to you	Attribution [5]

to kill as many opponents as possible. The bot difficulty level was set to 3 (hard) out of 4.

There was no upper limit on player score – the game terminated after a 3.5 minutes.

Players were equipped with only one weapon at a time – the AK-47 (the most popular automatic rifle) [12], with specifications as in Table 1, and unlimited ammunition.

To maximize combat compared to wandering, the third smallest [28] and most popular [11] map "Mirage" was used, depicted in Figure 2. The user and the bots spawned at random locations on the map that were not currently in view of anyone else.

All user movement (keyboard presses) and shooting (mouse button clicks) were logged with a custom tool called evlag.

The CS:GO settings were pre-configured at the server with the experiment controlled by scripts on the client – this meant when starting the study, users immediately joined and launched into the game, bypassing normal game lobbies and weapon selection phases.

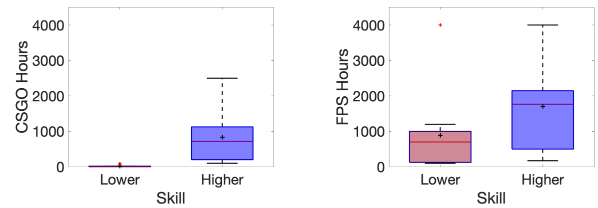
A user study proctor was available for questions and troubleshooting during the experiment.

Users first did a custom reaction-time test written in Javascript and launched via a Chrome Web browser. In the test, users waited for a screen color change then clicked the mouse as quickly as possible, doing this 10 times.

Users played a practice round without any added network latency to get familiar with the map and game mode. This round was not analyzed. Users then played additional 3.5 minute rounds of CS:GO, each round with a different network latency (25, 50, 100, or 150 milliseconds), randomly shuffled.

Table 3: Demographics

Skill	Users	Age	FPS Self-rating	CS:GO Self-rating	Reaction Time (ms)
Lower	11	21.0 (3.4)	4.4 (0.9)	2.5 (0.9)	204 (29)
Higher	25	20.8 (3.0)	4.4 (0.7)	4.6 (0.5)	205 (24)



(a) CS:GO Hours (b) FPS Hours

Figure 3: Self-reported playtime

After each round, users filled out a subjective survey consisting of nine questions on a discrete 5-point Likert scale about the game experience in the preceding round. The abbreviated questions are shown in Table 2, with the complete text available online.[2]

After completing the survey, the next round would commence when the user was ready.

After completing all the game rounds, users were given a questionnaire with additional demographics questions.

The IRB-approved user study was conducted during the COVID pandemic, so everyone wore masks and respected social distancing requirements. Upon completion of each user's study, we carefully sanitized the keyboard, mouse and earphones.

Study participants were solicited via University email lists. Interested participants first filled out a screener questionnaire to ascertain FPS and CS:GO experience (hours and self-rated score). Users were rewarded with a $10 USD Amazon gift card upon completion of the study.

4 RESULTS

Thirty-six (36) users were screened to participate in the user study out of 128 initial responses. All selected participants reported playing at least 100 hours of FPS games. However, in terms of CS:GO skill, we dub 24 players "higher-skill" since they reported having played more than 100 hours in CS:GO, and the other 11 players "lower-skill" since most of reported no CS:GO experience and all reported fewer than 100 hours in CS:GO.

Table 3 summarizes the participant demographics. FPS self-rating and CS:GO self-rating are on a five-point scale, 1 (low) to 5 (high). For age, FPS self-rating, CS:GO self-rating, and reaction time, the mean values are given with standard deviations in parentheses. Ages ranged from 17-29 years old for the higher-skill group and 18-28 for the lower-skill group, typical of a University subject pool. All participants were male – while disappointed there were no female participants, we note FPS esports players tend to be mostly

[2]https://web.cs.wpi.edu/~claypool/papers/csgo-skill-21/

males [27]. For both skill groups, user self-ratings as FPS players skew towards "high" and have identical means – 4.4 out of 5. For CS:GO self-ratings, however, the higher-skill group has a mean rating of 4.6 compared to only a 2.5 for the lower-skill group. Reaction times are mostly fast for both groups of players – largely between 195 and 220 ms – typical of experienced computer game players [7].

Figures 3a and 3b depict boxplot distributions for CS:GO hours played and FPS hours played, respectively. Both boxes depicts quartiles and medians for the distributions. Points higher or lower than 1.4 × the inter-quartile range are outliers, shown by red pluses. The whiskers span from the minimum non-outlier to the maximum non-outlier. The black pluses shows the mean values. Within the higher-skill group, most users played 500-2250 hours of FPS games and 100-1100 hours of CS:GO. One player reported 20,000 hours of FPS play, and that single data point is removed from Figure 3b. Within the lower-skill group, most users played 100-1200 hours of FPS games and 0-50 hours of CS:GO.

The grouping of users into higher-skill and lower-skill groups based on the self-reported ratings and hours played is supported by overall performance in our user study. An independent t-test of score shows the 25 higher-skill participants have better scores (M=12.3 points/min, SD=1.6) compared to the 11 lower-skill participants (M=15.5 points/min, SD=1.6) ($t(34) = -4.0$, $p = .02$).

5 ANALYSIS

This section compares the effects of network latency on higher-skill players and lower-skill players for performance (Section 5.1) and Quality of Experience (Section 5.2).

5.1 Performance

We measure user performance in terms of accuracy (shots hit divided by shots fired) and score (in CS:GO, $score = 2 \times kills + assists$). The CS:GO log files are mined to determine number of hits, kills and assists by each user for each round, and the evlag log files provide the shots fired based on the number of left mouse-button clicks.

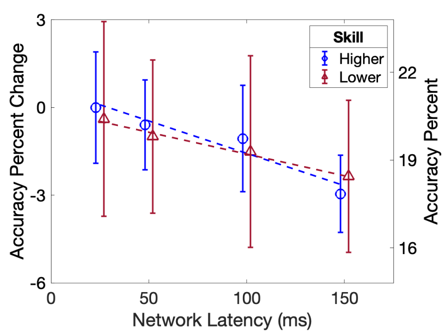


Figure 4: Accuracy (means with 95% ci)

5.1.1 Accuracy. Figure 4 depicts weapon accuracy versus latency. The x axis is the network latency. The y axis is the weapon accuracy (percent) decrease from the 25 ms network latency condition of the higher-skill group. For example, an accuracy of 20 percent at 25 ms of latency compared to an accuracy of 15 percent at 125 ms of latency would be a 5 percent decrease. The points are the means for all users for that latency condition, bounded by 95% confidence intervals. The dashed lines show a linear regression for the mean values. The blue points and lines denote the higher-skill users, and the red denotes the lower-skill users.

The regressions fit the means well for both group of users, with an R^2 of 0.98 and $p = .009$ for the lower-skill group, and an R^2 of 0.93 and $p = .038$ for the higher-skill group. Visually, the higher-skill slope is slightly steeper than the lower-skill slope indicating network latency has a greater effect on accuracy for higher-skill players than for lower-skill players. As a take-away, a decrease in network latency by 100 ms decreases accuracy for higher-skill players by an average of about 2.2 percent, and lower-skill players by 1.5 percent – network latency has a 32% higher impact on accuracy for higher-skill players.

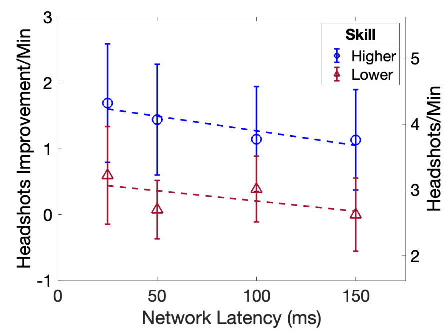


Figure 5: Headshots (means with 95% ci)

5.1.2 Boom, Headshot! While visually, the difference in accuracy slopes in Figure 4 for higher-skill users and lower-skill users may not be dramatic, what often matters is where hits land – shots to the arms and legs do far less damage than shots to the head. For reference, a single headshot with an AK-47 in a CS:GO game will kill a full health opponent.

Figure 5 depicts the total number of headshots per minute versus latency. The axes and points are as for Figure 4 but here the y axes are headshots instead of accuracy. The regression fits the means well for the higher-skill group, with an R^2 of 0.84 and $p = .08$. However, the regression fits the lower-skill group less well, with an R^2 of 0.39 and $p = .38$, likely owing to the smaller sample size. Note the average number of headshots for the lower-skill group is higher at 100 milliseconds of latency than the average at 50 milliseconds of latency.

Visually, the slopes for both groups are clearly separate, with the higher-skill group getting about 50% more headshots per round than the lower-skill group. The slopes look visually similar, but are actually slightly steeper for the higher-skill group (-0.003 versus -0.004). As a take-away, a increase in network latency by 100 ms decreases the number of headshots landed by higher-skill players by an average of about 0.4 per minute, and lower-skill players by 0.3 per minute – network latency has a 25% higher impact on the number of headshots for higher-skill players. Higher-skill players hit 50% more headshots per game than lower-skill players.

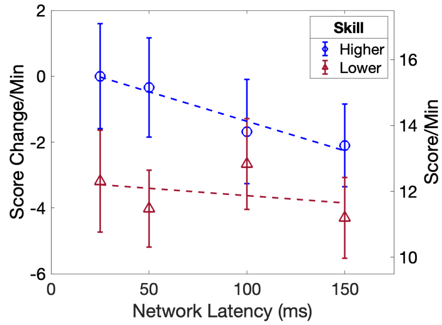


Figure 6: Score (means with 95% ci)

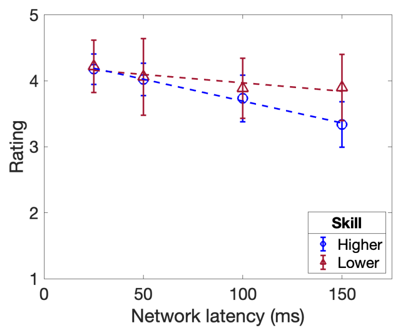


Figure 7: QoE (means with 95% ci)

5.1.3 Score. Figure 6 depicts player score versus latency. The axes and points are as in Figure 4, but the data is the score ($2 \times kills + assists$) per minute instead of accuracy. The regression fits the means well for the higher-skill group, with an R^2 of 0.93 and $p = .023$. However, the regression fits poorly for the lower-skill group, with an R^2 of 0.11 and $p = .67$, again probably due to the smaller sample size and high point at latency 100 ms for the lower-skill group.

Visually, the slope for the higher-skill group is steeper than the slope for the lower-skill group. As a take-away, a decrease in network latency by 100 ms degrades player score by about 2 points per minute for higher-skill players, and 0.4 points per minute for lower-skill players. For reference, often less than a single point separates the scores of the top CS:GO players in a game.

5.2 Quality of Experience

Quality of Experience (QoE) was assessed from responses to the 9 survey questions, filled out by users at the end of each round. Responses are on a discrete 5-point scale and for the analysis, and the data is aligned so a 1 is low (worse) and a 5 is high (better).

Analysis of mean scores for each question shows QoE degrades with network latency for each individual question for both groups of users. For the higher-skill group, the linear regressions fit the means well for all questions, with R^2 values from 0.90 to 0.99, but for the lower-skill group, the R^2 values have a larger range, from 0.11 to 0.90.

Table 4: Linear regression for latency separated by skill

Metric	Group	Coeff.	Intercept	R^2	P value
Accuracy	Low	-0.015	20.70	0.98	**.009**
Accuracy	High	-0.022	21.45	0.93	**.038**
Score	Low	-0.004	12.32	0.11	.67
Score	High	-0.017	15.92	0.96	**.023**
QoE	Low	-0.003	4.22	0.80	.105
QoE	High	-0.006	4.36	0.99	**.007**

Table 5: Linear regression for latency and skill

Metric	Skill Coeff.	Latency Coeff.	R^2	Intercept	Skill p value	Latency p value
Accuracy	0.16	-0.019	0.91	20.99	0.55	**.001**
Score	2.51	-0.011	0.86	12.86	**.004**	.084

For an overall measure of QoE, we compute the mean combined rating, weighting all questions equally. Figure 7 depicts the results. The x axis is the network latency in milliseconds and the y axis is the rating. The points are the means for all users for that latency condition, bounded by 95% confidence intervals. The dashed lines are linear regression fits through the mean values. The blue represents the higher-skill group and the red represents the lower-skill group. The linear regressions fit the means well for both groups, with R^2 0.80 and $p = .105$ for the lower-skill group and R^2 0.99 and $p = .007$ for the higher-skill group.

Visually, the QoE values are similar for the two groups at 25 milliseconds of latency, but the impact of latency is greater for the higher-skill group than the lower skill group as evidenced by the steeper slope. As a take-away, an increase in network latency by 100 ms degrades QoE by about 0.3 points on a 5-point scale for lower-skill players, and 0.6 points for higher-skill players – network latency has twice the impact on QoE for the higher-skill players.

5.3 Summary

Table 4 summarizes the linear regressions from the above analysis in tabular form. The regressions fit the mean values well and all results are significant for the higher-skill group, while score and QoE are not significant for the lower-skill group. The regression slopes for the higher-skill group are steeper than the regression slopes for lower-skill group for all cases.

Table 5 depicts the results of unified model, showing linear regression of player performance versus skill and latency, where higher skill is coded as 1 and lower skill as 0. The regressions fit the mean values well, skill is not significant for accuracy but is for score, with the converse for latency.

6 LIMITATIONS

Our user study intentionally focuses on the effects of latency on individual player performance. However, as noted in Section 3, CS:GO is often a team game, where groups of players (typically 5 per team in esports) work together to defeat the opposing team. The impact of latency on CS:GO team efforts, perhaps even team strategies, was not assessed.

Our study has only 11 players in the lower-skill group. While this is more than some other published studies of player skill and games, the small sample size limits the statistical power of the results.

As noted in Section 4, our study is skewed towards males (no females participated). While this may reflect the gender breakdown of FPS games today, the results may not be indicative of female performance in competitive FPS games.

Our study intentionally isolated CS:GO play to a single weapon type only – the most popular [12] AK-47 rifle – whereas players typically can choose from a variety of weapons with different firing rates, magazine capacities and damages inflicted.

Most CS:GO games use only human players and not AI-controlled bots. While it is likely that the absolute scores observed would differ for users pitted against human players, the relative effects should be similar since the latency affects the ability to aim and shoot (thus, score and accuracy).

7 CONCLUSION

Many game players pay attention to network latencies ("ping" times to gamers), but how much network latencies impact players based on skill is not well-known. Understanding the impact of network latency by player skill may better inform gamers about the need to upgrade their network connections and motivate developers and researchers to devise tools and systems to mitigate network latency for games and game-like applications.

We study the effects of network latency on the first-person shooter (FPS) game *Counter-strike: Global Offensive (CS:GO)* (Valve, 2012) comparing and contrasting two groups of players: *higher-skill* – those with extensive FPS experience and considerable CS:GO experience, and *lower-skill* – those with extensive FPS game experience but little or no CS:GO experience. We setup a testbed that allowed for CS:GO play with controlled amounts of latency, gathering objective data (player performance) through logs and subjective data (Quality of Experience) through surveys. Thirty-six (36) users (25 higher-skill and 11 lower-skill) each played rounds of CS:GO with four different latency conditions: 25, 50, 100 and 150 milliseconds.

Based on our analysis, network latency has more impact – both player performance and player Quality of Experience – on higher-skill players than on lower-skill players. In general, for CS:GO with 25 milliseconds of network latency: (A) for higher-skill players, an increase of 100 ms of network latency decreases accuracy by 2.2 percent, score by 2 points per minute, and QoE by 0.6 points (out of 5), while (B) for lower-skill players, an increase of 100 ms of network latency decreases accuracy by 1.5 percent, score by 0.4 points per minute and QoE by 0.3 points. Put it another way, for higher-skill players network latency has fifty-percent more impact on accuracy, five-times the impact on score, and twice the impact on QoE than for lower-skill players.

Future work may compare the performance and QoE of players in different skill pools and for additional game aspects and configurations, such as local latency (rather than network latency), player versus player (rather than versus bots), other weapon types (e.g., snipers), and team composition (considering team skill).

REFERENCES

[1] R. Amin, F. Jackson, J. Gilbert, J. Martin, and T. Shaw. 2013. Assessing the Impact of Latency and Jitter on the Perceived Quality of Call of Duty Modern Warfare 2. In *Proceedings of HCI – Users and Contexts of Use*. Springer-Verlag, Berlin, Heidelberg.

[2] G. Armitage. 2003. An Experimental Estimation of Latency Sensitivity in Multiplayer Quake 3. In *Proceedings of IEEE ICON*. Sydney, Australia.

[3] T. Beigbeder, R. Coughlan, C. Lusher, J. Plunkett, E. Agu, and M. Claypool. 2004. The Effects of Loss and Latency on User Performance in Unreal Tournament 2003. In *Proceedings of ACM NetGames*. Portland, OG, USA.

[4] M. Claypool. 2018. Game Input with Delay - Moving Target Selection with a Game Controller Thumbstick. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) - Special Section on Delay-Sensitive Video Computing in the Cloud* 14, 3s (Aug. 2018).

[5] A. Depping and R. Mandryk. 2017. Why is This Happening to Me?: How Player Attribution Can Broaden Our Understanding of Player Experience. In *Proceedings of ACM CHI*. Denver, CO, USA.

[6] M. Dick, O. Wellnitz, and L. Wolf. 2005. Analysis of Factors Affecting Players' Performance and Perception in Multiplayer Games. In *Proceedings of ACM NetGames*. Hawthorn, NY, USA.

[7] M. Dye, C.S. Green, and D. Bavelier. 2009. Increasing Speed of Processing with Action Video Games. *Current Directions in Psychological Science* 18, 6 (Dec. 2009), 321–326.

[8] T. Fritsch, H. Ritter, and J. Schiller. 2005. The Effect of Latency and Network Limitations on MMORPGs: a Field Study of Everquest 2. In *Proceedings of ACM NetGames*. Hawthorne, NY, USA.

[9] Google. 2020. Google Stadia Post-game Survey. stadia. https://stadia.google.com/ (Accessed Oct 15, 2021).

[10] C. Gough. 2020. eSports Audience Size Worldwide from 2018 to 2023. Statista. Online: https://tinyurl.com/y3tffxzo. (Accessed September 17, 2020).

[11] HLTV. 2020. CS:GO Statistics Database – Distribution of Maps Played. hltv.org. https://www.hltv.org/stats/maps (Accessed September 17, 2020).

[12] HLTV. 2020. CS:GO Statistics Database – Top Weapons. hltv.org. https://www.hltv.org/stats?startDate=all (Accessed September 17, 2020).

[13] O. Hossfeld, H. Fiedler, E. Pujol, and D. Guse. 2016. Insensitivity to Network Delay: Minecraft Gaming Experience of Casual Gamers. In *Proceedings of the International Teletraffic Congress (ITC)*. IEEE, Würzburg, Germany.

[14] Z. Ivkovic, I. Stavness, C. Gutwin, and S. Sutcliffe. 2015. Quantifying and Mitigating the Negative Effects of Local Latencies on Aiming in 3d Shooter Games. In *Proceedings of ACM CHI*. Seoul, Republic of Korea.

[15] J. Jansz and M. Tanis. 2007. Appeal of Playing Online First Person Shooter Games. *Cyberpsychology & Behavior* 10, 1 (2007).

[16] W.K. Lee and R. Chang. 2015. Evaluation of Lag-Related Configurations in First-Person Shooter Games. In *Proceedings of ACM NetGames*. Zagreb, Croatia.

[17] S. Liu, A. Kuwahara, J. Scovell, J. Sherman, and M. Claypool. 2021. Lower is Better? The Effects of Local Latencies on Competitive First-Person Shooter Game Players. In *Proceedings of ACM CHI*. Yokohama, Japan, 12 pages.

[18] M. Long and C. Gutwin. 2018. Characterizing and Modeling the Effects of Local Latency on Game Performance and Experience. In *Proceedings of ACM CHI Play*. New York, NY, USA.

[19] M. Long and C. Gutwin. 2019. Effects of Local Latency on Game Pointing Devices and Game Pointing Tasks. In *Proceedings of ACM CHI*. Glasgow, Scotland, UK.

[20] I. Makarov, D. Savostyanov, B. Litvyakov, and D. Ignatov. 2017. Predicting Winning Team and Probabilistic Ratings in 'Dota 2' and 'Counter-Strike: Global Offensive' Video Games. In *Proceedings of Springer AIST*. Moscow, Russia.

[21] Lothar Pantel and Lars C. Wolf. 2002. On the Impact of Delay on Real-Time Multiplayer Games. In *Proceedings of NOSSDAV*. Miami, Florida, USA.

[22] K. Poels, Y.A.W. de Kort, and W.A. IJsselsteijn. 2007. *D3.3 : Game Experience Questionnaire: Development of a Self-report Measure to Assess the Psychological Impact of Digital Games.* Technische Universiteit Eindhoven.

[23] P. Quax, P. Monsieurs, W. Lamotte, D. De Vleeschauwer, and N. Degrande. 2004. Objective and Subjective Evaluation of the Influence of Small Amounts of Delay and Jitter on a Recent First Person Shooter Game. In *Proceedings of ACM NetGames*. Portland, OG, USA.

[24] Reuters.com. 2018. Investing in the Soaring Popularity of Gaming. Online: https://www.reuters.com/sponsored/article/popularity-of-gaming. (Accessed September 17, 2020).

[25] R. Ryan, C. S. Rigby, and A. Przybylski. 2006. The Motivational Pull of Video Games: A Self-determination Theory Approach. *Motivation and Emotion* 30, 4 (2006), 344–360.

[26] N. Sheldon, E. Girard, S. Borg, M. Claypool, and E. Agu. 2003. The Effect of Latency on User Performance in Warcraft III. In *Proceedings of ACM NetGames*. Redwood City, CA, USA.

[27] Statista. 2020. Distribution of Gamers Playing Selected Game Genres Worldwide as of January 2017, by Gender. Online: https://tinyurl.com/yytrbj4d. (Accessed September 17, 2020).

[28] u/khaniage. 2019. Counter-strike: Global Offensive – Map Sizes. Reddit. https://www.reddit.com/r/GlobalOffensive/comments/a94jba/map_sizes/ (Accessed September 17, 2020).