Effects of Frame Rates up to 500 Hz on First Person Shooter Game Players

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Computer games – and computer game players – often drive technology improvements, with graphics cards and monitors pushing the limits of display technologies. High frame rates, in particular, promise to provide lower latencies and smoother game visuals to gamers, especially important for competitive first-person shooter (FPS) game players. What is not well-known is to what extent gamers benefit from ultra-high frame rates in terms of player performance and quality of experience. This paper studies the effects of frame rates – especially high frame rates – on FPS game players. We developed a custom FPS game that provides a consistent delivery of frame rates from 7 f/s to 500 f/s, while recording objective (performance) and subjective (smoothness) measures. Analysis of data from a 44-person user study shows player performance (e.g., score and accuracy) improves sharply from 7+ f/s, but levels out after about 90 f/s. However, users' perception benefits over the full range of frame rates studied, rising sharply from 7+ f/s, and continuing to improve through 500 f/s. In addition, we compare our results with prior work assessing the effects of frame rates across multiple controlled game tasks, finding common trends in the low-to-mid frame rate ranges for most tasks, with a few notable differences.

CCS Concepts: • **Applied computing** → **Computer games**; • **Human-centered computing** → *User studies*; Laboratory experiments.

Additional Key Words and Phrases: First Person Shooter, FPS, High Refresh Rate, Frame Rate, 500 Hz, Latency, QoE, Quality of Experience, Visual Perception

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1 INTRODUCTION

Computer games continue to drive many advances in computer technologies with improvements to hardware and supporting software enhancing both player immersion and player performance [6]. In first-person shooter (FPS) games, precision and responsiveness are essential, and high frame rate monitors driven by powerful GPUs are sought out by competitive esports players [12]. High frame rates provide smoother animations and reduce input latency, potentially boosting player experience and performance.

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Figure 1 shows a sequence of frames representing the movement of an avatar on the screen over time.[1] Higher frame rates provide more visual changes per second, each capturing small position changes and making transitions between frames smaller and smoother.

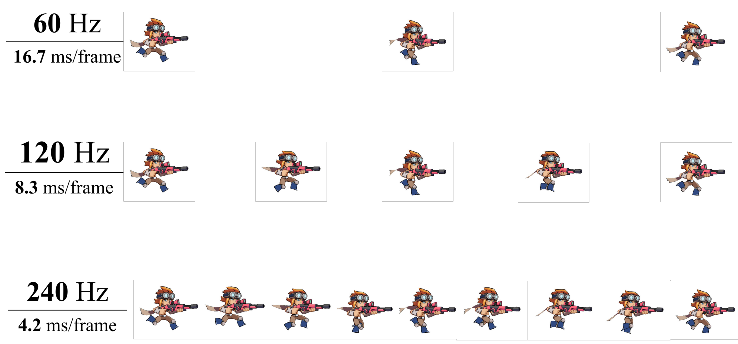


Fig. 1. Visual smoothness and frame rate. Each row shows the same avatar movement rendered at a different frame rate (60, 120, and 240 Hz). At higher frame rates, more frames are presented per second, so each frame captures a smaller change in the avatar's animation and position, and motion appears smoother to the player.

Higher frame rates also bring the benefits of lower input latencies helping players see actions sooner. Figure 2 shows the same in-game event – an avatar emerging from the right edge of the screen – as it would be seen at three different frame rates (60, 120, and 240 Hz). Each green block represents one rendered frame; the avatar appears once a frame is presented that captures it on screen. The higher frame rates show frames more frequently so the avatar becomes visible to the player earlier (further to the left along the time axis), reducing the time between visual updates and the system latency. This allows the player to see changes earlier (e.g., an opponent emerging from cover), giving them more time to react and a competitive advantage. However, the benefits of higher frame rates must be considered in the context of the base latency of the system – if a display or rendering pipeline introduces substantial additional latency (e.g., TV-like image post-processing), gameplay can suffer even with high frame rates.

Despite the availability of high-end gaming systems for consumers, the extent to which high frame rates affect player performance and quality of experience (QoE) in FPS games remains under-explored. Understanding the impact of high frame rates on players can help: 1) system developers focus on technologies that matter to players, and 2) players decide on upgrades or settings that meaningfully affect their play.

To study the effects of high frame rates on FPS game players, we designed and implemented a bespoke FPS game – *Lead Rush* – that focuses on core FPS mechanics while supporting frame rates up to 500 f/s. Participants played Lead Rush for about two dozen short rounds at different frame rates while logging performance metrics (e.g., shots fired, shots hit) and smoothness ratings. This setup enabled analysis of how frame rate affects both player performance and QoE, with an earlier version of this analysis published in the NOSSDAV 2025 workshop [16].

This paper extends that work with: 1) additional analysis of the user study results, and 2) a comparison of our findings with prior work on the effects of frame rates across a variety of controlled game or game-like tasks including: a) shooting in commercial and custom FPS games, b) moving target selection, c) latency-controlled aiming, and d) virtual reality interaction. We extract data

[1]Base character animation artwork sourced from: https://www.behance.net/gallery/107905859/Character-2D-animation-run-and-gun/modules/618460599.

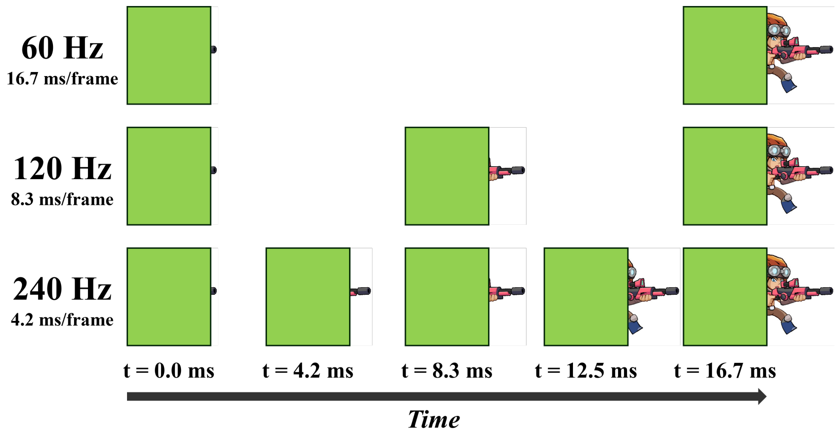


Fig. 2. System latency and frame rate. Each row shows the same in-game event (an avatar emerging from the right) as it would be presented at 60, 120, and 240 Hz. The horizontal axis is time and each block is one rendered frame. At higher frame rates, frames are presented more frequently, so the avatar becomes visible to the player sooner, allowing more time to react.

from the main results from these prior studies, and visually compare where the effects of frame rates in our study align with / or deviates from these other studies.

The rest of this paper is organized as follows: Section 2 provides background and related research; Section 3 describes the study methodology; Section 4 analyzes the results; Section 5 compares our results with other frame rate studies; Section 6 outlines study limitations; and Section 7 concludes the paper.

2 RELATED WORK

This section summarizes studies related to our work in three areas: frame rates and visual quality (Section 2.1), frame time variability (Section 2.2), and frame rates and FPS games (Section 2.3).

2.1 Frame Rate and Visual Quality

Frame rate is a common Quality of Experience (QoE) metric, and its relationship with media quality has been studied across various types of video. Early work by Apteker et al. [1] analyzed the influence of network bitrates on video playback rates. They found that reduced bitrates degraded video quality by lowering the playback frame rate, but streaming software at that time did not automatically adapt frame rate to bitrate. Mazhar and Abdalla [11] studied the tradeoff between frame rate and resolution and concluded that at least 20 f/s were needed for high-motion sequences, but 15 f/s may be acceptable for low-motion sequences. Across both studies, playback rates for video content impacted performance and quality.

Ou et al. [14] found that video quality decreased as frame rates dropped following an inverted exponential trend, with faster motion content degrading more quickly. They proposed a model to predict quality based on motion, frame differences, and contrast, emphasizing the need for higher frame rates to maintain quality in dynamic content.

Zadtootaghaj et al. [24] developed a QoE model for cloud gaming that focused on the relationship between bitrates and framerates. They concluded that for lower bitrates, opting for a frame rate of 25 f/s was advisable to minimize blockiness in the video. However, at frame rates below 25 f/s, video quality significantly deteriorated due to jerkiness, which could potentially lead to fatigue or other adverse effects over time.

2.2 Frame Time Variation and Adaptive Displays

In FPS games, players rely on real-time visual cues to aim and react, making frame rate and inter-frame variability critical. Klein et al. [8] found that significant deviations from the average frame time affected how smooth the motion appeared to users, however these deviations minimally impacted other aspects of performance or experience.

Liu et al. [10] showed that increased frame time variability – induced by higher CPU load in the commercial games Valorant, Rocket League, and Strange Brigade – reduced the quality of experience.

Event-specific frametime spikes have also been shown to reduce player performance and experience in an FPS game when they occur during high-impact events such as targeting [17]. This was extended to 2D platformer navigation tasks, where performance impacts depend on the difficulty of the task [19].

Technologies like VSync and G-Sync help mitigate these effects. Lee et al. [9] focused on two key aspects in their study on VSync in FPS gameplay: server tick-rate, which is the frequency at which a server updates game data, and VSync, which matches frame rates with a monitor's refresh rate to reduce screen tearing. They found that both a higher server tick-rate and the use of VSync led to improved player accuracy.

Watson et al. [22] conducted a preliminary study on the effects of G-Sync, which dynamically synchronizes the display's refresh rate with the graphics card's frame rate for smoother gameplay. Their research revealed that adaptive synchronization enhanced gaming performance in the commercial FPS game Battlefield 4.

Xu et al. [23] developed a QoE model from four studies over 11 games considering frame rate and frame time variations. They found that frame time variability and interruption severity were strong predictors of player experience, accounting for roughly 90% of gaming quality variance, though average frame rate did not always predict satisfaction accurately.

Wang et al. [21] showed that frame rate in virtual reality significantly affected both user experience and task performance in a "Fruit Cutting" game, with associated impacts and benefits to motion sickness across 60-180 f/s.

Denes et al. [5] developed a model to optimize motion quality by adjusting monitor refresh rates and resolutions based on motion speed. Their experiments, ranging from 50 f/s to 165 f/s, showed that adaptive refresh rates provided smoother visuals than fixed rates, especially for fast-moving content. The study highlighted that balancing refresh rate and resolution improved performance, with practical applications for G-Sync monitors and VR/AR headsets for better visual quality with hardware limits.

2.3 Impact of Frame Rate on FPS Games

Claypool and Claypool [2] examined how varying frame rates impact player performance through the lenses of first person, third person, and isometric avatar perspectives. Generally, when the frame rate dropped below 15 f/s, users performed worse, especially in tasks that required quick, precise actions like shooting in games. The negative impact on performance was more noticeable for actions needing fast, accurate responses compared to tasks that can handle a bit of delay, like moving around in the game.

In a comparative study between frame rate and resolution, Claypool et al. [3, 4] found that frame rate had a greater impact on player performance and perceived game quality than did resolution. They also observed that for video playback, the situation was reversed: resolution was more important to viewers than frame rate.

Spjut et al. [15] studied the effects of latency and display refresh rates on FPS performance for skilled esports athletes. They found that lower latency significantly improved task times for both single-click ("1-hit") and tracking tasks. While higher refresh rates (120 f/s to 360 f/s) helped players for both tasks, the impact was greater for tracking tasks that required sustained aim and less so for single-click actions. A main benefit of higher refresh rates was their ability to reduce latency, which is important in competitive gaming.

Complementing these results, Janzen and Teather [7] examined the impact of frame rates for moving target selection with a mouse and found player performance at 60 f/s was about 14% higher than at 30 f/s, while player performance at 45 f/s and 60 f/s was not significantly different; moreover, frame rate exerted a larger effect than the benefits to latency alone implied.

Our current paper: extends previous research by focusing on ultra-high framerates, up to 500 f/s in a genre popular with previous studies and esports players – an FPS game. Unlike prior studies that adjusted input latency – an aspect inherently tied to frame rate – our research isolates frame rate as the primary factor of interest and evaluates the effects of frame rate on objective performance metrics (e.g., accuracy, score), subjective QoE (smoothness), and player behavior (e.g., mouse movement).

3 METHODOLOGY

To investigate the effects of frame rate in an FPS game, we conducted a user study using a custom FPS game called *Lead Rush*. The game was modified to fit our study, running each round at a controlled framerate while recording objective player performance and subjective Quality of Experience (QoE).

3.1 Game Description

Lead Rush [18][2] is a first-person shooter game developed in Unity 2023 to run at ultra-high frame rates (1500+ Hz). It features procedural animations, positional audio for gunplay, and a configurable system for controlling round settings (e.g., frame rate, round duration) and collecting data. A logging system was added to record performance metrics.

The game involves controlling an avatar to shoot and destroy an enemy, encountered one at a time, while avoiding contact. The Enemy is a floating red orb that requires 5 hits to destroy. The orb moves toward the player, navigating around obstacles. If it collides with the player, both are eliminated, and the player respawns at the starting position. After an orb is destroyed, a new one respawns in 100 milliseconds.

The orb's respawn location is dynamically set within a torus-shaped area, 4 to 6 Unity meters from the player, avoiding blocked areas. The orb oscillates on the Y-axis between 0.9 and 1.1 Unity meters and moves at 3.1 meters per second, slightly faster than the player's 3 meters per second. A Unity Navmesh[3] is used for navigation.

The game provides visual and audio cues for enemy direction and proximity. Yellow bars flash along the screen edges, growing brighter as the enemy gets closer. Positional audio indicates enemy location, with distinct sounds for hits, destruction, and shooting.

Figure 3 shows a screenshot of *Lead Rush*. The yellow bar at the top indicates the enemy is in front. Hit markers appear on successful hits (yellow) and kills (red), although these are not shown

[2]Lead Rush GitHub: https://github.com/Tokey/Lead-Rush
[3]Unity Navmesh: https://docs.unity3d.com/ScriptReference/AI.NavMesh.html

in the screenshot. The Lead Rush gameplay video[4] shows two rounds of gameplay. It demonstrates the gameplay mechanics, enemy AI, gunplay, animations, and UI elements in action. Each round ends with a window asking about visual quality via a slider to gather player feedback.

Fig. 3. Lead Rush in-game screenshot.

The study used a fully automatic assault rifle with a 750 rounds/minute (12.5 rounds/s) fire rate. Hits are detected via hitscan, and the gun features procedural recoil, sway, camera shake, and aim-down sight animations. A green laser assists aiming. The weapon has unlimited magazines of 31 bullets each and reloads automatically or manually (‘R’), with a 2-second reload animation. The player cannot shoot during reload.

Players earn 10 points per hit and 100 points per kill but lose 100 points per death. Scores can drop below zero.

3.2 Architecture and Latency

Lead Rush uses Unity’s standard game loop without modifications so has no additional latency beyond the underlying engine and operating system. Frame rate is controlled by setting `Application.targetFram` to the desired value for each round, rather than via manual frame pacing or sleep-based throttling in our code. This relies on Unity’s built-in frame rate limiting and ensures the engine itself manages the flow of the main loop.

Player input is handled through Unity’s default input system, which polls mouse and keyboard state once per frame. Mouse movement, button presses, and trigger pulls are read at the start of each frame and resolved within the same frame: camera rotation, weapon firing (via hitscan raycasts), and hit registration all occur in the same update cycle as the input that caused them. There is no additional input buffering, no fixed-timestep delay between input and resolution for these actions, and no special low-latency mouse handling beyond what Unity and the operating system provide by default.

Scene elements are updated each frame in Unity’s standard order: input is polled, game logic (enemy AI navigation via Navmesh, orb movement, collision checks, and scoring) executes, animations and procedural weapon effects (recoil, sway) are applied, and the frame is rendered and presented to the display. VSync is disabled, so frames are presented to the display as soon as they are rendered avoiding additional wait time for the next display refresh interval. Because Lead Rush runs well-above the monitor’s 500 Hz refresh ceiling at all tested frame rates up to 500 f/s, disabling VSync does not produce visible tearing within the conditions of our study.

[4]Lead Rush gameplay video: https://www.youtube.com/watch?v=Lakj7qhED1c

The end-to-end latency that results from this architecture – input, render, and display – is measured directly using the NVIDIA Reflex Analyzer and reported in Figure 4 (described below in Section 3.5). These measurements characterize the actual hidden latency present in *Lead Rush* beyond the average render delay of half the frame time alone.

3.3 Experimental Configuration

This study configured *Lead Rush* to run a fixed sequence of timed rounds at a controlled set of frame rates, prompting the user with a smoothness question after each round and writing per-round logs to disk. The remainder of this subsection describes those settings.

The game consists of 1-minute rounds played at different frame rates. This study explored twelve frame rates – 7, 15, 30, 45, 60, 75, 90, 120, 165, 240, 360 and 500 frames per second – each played twice for a total of 24 main rounds. Prior to the main rounds, participants played 2 practice rounds, each a minute long, with the first round at 500 f/s followed by a second round at 7 f/s. The order of the main rounds was arranged using a Latin square to balance frame rate conditions across sessions.

A session ID tracked each row of the Latin square. After a user completed a session, the session ID was incremented and saved to a file. For a new session (a new user), the ID was read from the file, and the corresponding row of the Latin square used to determine the sequence of rounds for that user.

After the round ended, players were asked a question regarding their experience for that round:

- *Rate the Smoothness of the Round* - 1 (Very Choppy) to 5 (Very Smooth) via a slider (0.1 increments).

The game generated logs to track player actions, performance metrics, and enemy interactions, which were used in our analysis.

3.4 User study procedure

The user study procedure was approved by the university's institutional review board. It began with recruitment through department emails and advertisements on an official Discord playtesting channel. Participants selected from availability time slots using Slottr. Before participating, each user read and signed a consent form outlining the study details and completed an optional demographic survey. A reaction time test was conducted, followed by two practice rounds – one at 500 f/s and another at 7 f/s – to familiarize participants with the highest and lowest frame rate conditions and the QoE question presented after each round. Participants then completed 24 main rounds. Log files from each session were collected and backed up by the study proctor. Each session lasted approximately 30 minutes, and participants were entered into a raffle for a $25 Amazon eGift card, with an additional $10 eGift card awarded to the highest scorer.

3.5 Hardware

The participant's computer was a high-end gaming PC: an ALIENWARE AW2524H monitor overclocked to 500 Hz, 1920x1080 pixels, an Intel Core i9-11900K CPU, 32 GB DDR4 RAM, an NVIDIA 4070 Super FE GPU, a Samsung 970 Evo SSD, and a Logitech G502 mouse. This PC allowed Lead Rush to run consistently at extremely high frame rates.

The NVIDIA Reflex Analyzer measured the local latency of our system. For the latency measurements only, *Lead Rush* was modified to display a color-changing box on the side of the screen upon mouse click. The mouse was connected to the monitor, and the game was played through 12 rounds with our 12 sets of frame rates.

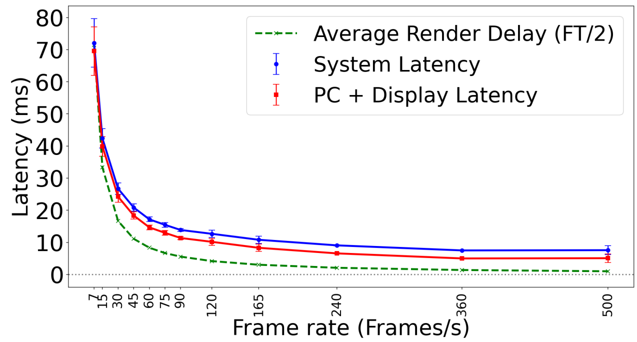


Fig. 4. Latency of Lead Rush using NVIDIA Reflex Analyzer. The blue and red points are mean measured latencies, shown with 95% confidence intervals. The green dashed line is the average render latency for the frame rate alone, computed as half the frame time.

Figure 4 presents a comparison of system latency, PC + display latency, and the estimated average render latency across different frame rates. The data was measured using NVIDIA GeForce Experience (Version 3.28.0.412 - Experimental) and reported as means with 95% confidence intervals. The blue line shows the system latency, which is the total time taken for the computer to process an input and display the corresponding action on the screen. The red line represents the PC + display latency, a component of system latency, measured from when the OS registers the click to when the display updates. The green dashed line shows the average render delay (FT/2), where FT is the frame time for a given frame rate. The average render delay is shown as an estimate of the minimum latency an event experiences based on the frame rate. An input event can arrive at any point during a frame's rendering cycle with roughly uniform probability, so if an input arrives just after a frame is displayed, it must wait the full frame time (FT) before being displayed, but if an input arrives just before the frame is presented, the wait approaches zero. Averaging across all possible arrival times within the frame yields an expected latency of FT/2.

The graph shows the PC provides consistent control of the frame rate for the full range of frame rate studied (7 - 500 f/s) with small system and display latencies on top of the average frame time latency. The recorded frame rates were close to the intended values, with minimal deviations. Lower frame rates (7 to 75 f/s) had standard deviations of 0.00 to 0.01, while higher rates (90 to 500 f/s) showed only slightly more variation, with deviations from 0.02 to 0.15. This shows the hardware maintained the intended frame rates.

4 ANALYSIS

This section provides the participant demographics (Section 4.1), followed by an analysis of Lead Rush player experience (Section 4.2), performance and behavior (Section 4.3), and ending with a comparative analysis of other work (Section 5).

4.1 Demographics

A total of 44 players participated in the user study. Table 1 summarizes their demographics. Numeric values are means with standard deviations in parentheses. The average participant age was about 21 years (M = 21.6, SD = 5.5), ranging from 18 to 38 years old, with the majority identifying as male (68%). Participants rated their experience in general gaming and FPS games with a mouse and keyboard on a scale from 1 (low) to 5 (high). On average, participants had moderate gaming experience (M = 3.3, SD = 0.9) and moderate FPS experience (M = 2.9, SD = 1.1) and enjoyed

Table 1. Participant demographics. Age, skill, reaction time and "likes" are mean values with standard deviations in parentheses.

Users	**Age**	**Gender**	**Gaming Skill** (1-5)	**FPS Skill** (1-5)	**Reaction Time** (ms)	**Likes Games** (1-5)
44	21.6 (5.5)	♂30 ♀12 ☿2	3.3 (0.9)	2.9 (1.1)	196.5 (72.0)	4.4 (0.7)

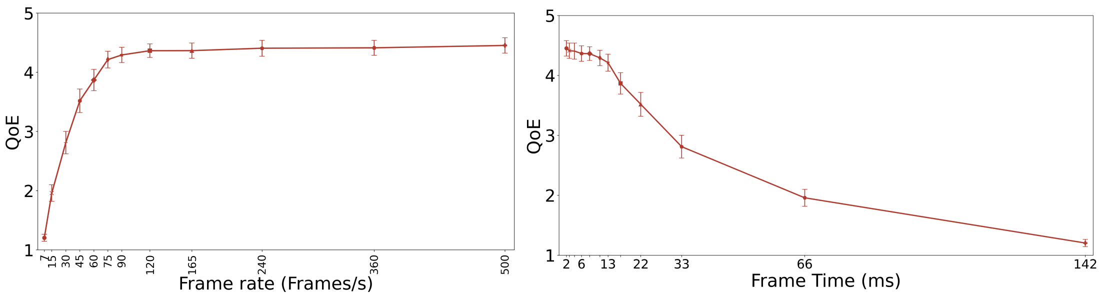


Fig. 5. Player experience (QoE) versus frame rate (left) and frame time (right). Each point is the mean QoE rating (1 = Very Choppy, 5 = Very Smooth) across all rounds at that frame rate / frame time, and error bars are 95% confidence intervals.

playing games (M = 4.4, SD = 0.7). Reaction times were quick (M = 196.5 ms, SD = 72.0), typical of experienced gamers.

4.2 Player Experience

Figure 5 shows the QoE scores for all users over all rounds, with means bounded by 95% confidence intervals. The graph on the left shows QoE versus frame rate on the x-axis and the graph on the right shows the same QoE data, but plotted versus frame time – the time between two subsequent frames (e.g., 100 f/s has a frame time of 10 ms) – on the x-axis. Frame time is just the reciprocal of frame rate: frame rate is frames per second, while frame time is milliseconds per frame. The frame rate graph allows for closer scrutiny of the high frame rates (low frame times), while the frametime graph better illustrates the low frame rates (high frame times). From the graph on the left, there is a sharp increase in QoE as frame rates go from 7 f/s to about 90 f/s then a noticeable flattening of the QoE trends from 120 f/s to 500 f/s. From the graph on the right, the trend in decreasing QoE scores with an increase in frame time that is fairly linear across all frame rates, albeit with a slight curve from 13 ms to 142 ms. Note, in both graphs, while the QoE trends have flattened, there appears to be a slight upward slope even at the highest frame rates – a slight increase in QoE at the right edge of the left graph from 165 f/s to 500 f/s and a slight decrease in QoE at the left edge of the right graph from 2 to 13 ms. This suggests that players are able to notice the smoother experience afforded by the highest frame rates.

4.3 Player Performance

This subsection presents an analysis based on score, which provides an aggregate measure of player performance, and on accuracy, which provides a lower-level performance measure.

4.3.1 Score. Figure 6 shows the scores for all users averaged across all rounds with 95% confidence intervals. The left graph shows score versus frame rate and the right graph shows the same data but versus frame time. From the graph on the left, player performance rises sharply from 7 f/s to 60

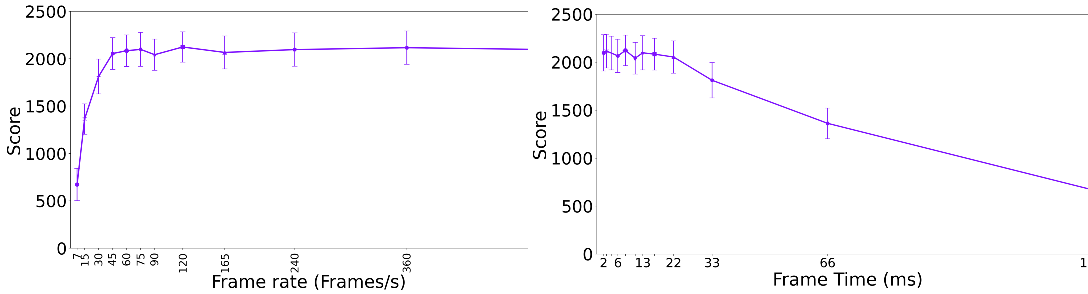
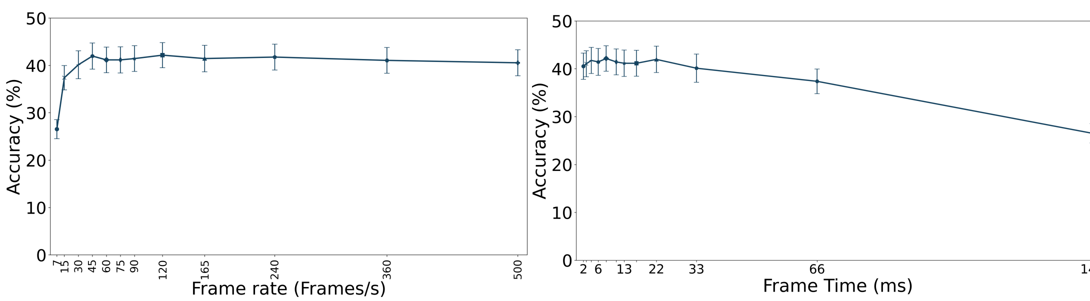


Fig. 6. Player performance (score) versus frame rate (left) and frame time (right). Each point is the mean per-round score across all rounds at that frame rate, and error bars are 95% confidence intervals. Scoring rules: +10 per hit, +100 per kill, −100 per death (scores can go negative).



(a) Accuracy over frame rate.

(b) Accuracy over frame time.

Fig. 7. Player performance (accuracy, % of shots that hit) versus frame rate (left) and frame time (right). Each point is the mean accuracy across all rounds at that frame rate, and error bars are 95% confidence intervals. Accuracy rises sharply from 7 to 45 f/s and is essentially flat above 45 f/s.

f/s and then flattens, showing almost no change from 60 f/s to 500 f/s. This is evident in the flat trend on the left side of the right graph. Also in the right graph, the decrease in score is nearly linear as frame times increase from 22 ms to 142 ms.

4.3.2 Accuracy. Figure 7 shows performance analysis using accuracy (shots hit versus shots fired, reported as a percent), with axes the same as in Figure 6. The same trends hold for accuracy as for score, albeit with a bit less of a visual increase in accuracy for the lowest frame rates (7 f/s to 45 f/s on the left graph) and highest frame times (22 ms to 142 ms on the right graph). This suggests that the performance differences across frame rates are not due to strategy (i.e., a change in player tactics based on the frame rates) but is instead due to a performance impact for the lower-level action of aiming.

4.4 Statistical Significance

To identify where frame rate gains stop being meaningful, we ran Welch's t-tests on each adjacent pair of frame rates for Score, Accuracy, and QoE. Welch's is used because variances differ across conditions, particularly for QoE near the ends of the 1–5 scale. Table 2 reports the mean difference, t-statistic, degrees of freedom, p-value, and Cohen's d for each statistically significant pair.

Score gains are significant only at the two lowest transitions (7 vs. 15 and 15 vs. 30 f/s), 30 vs. 45 f/s is close ($p = 0.055$), and nothing above it has a statistically significant difference. Accuracy has

Table 2. Welch's t-tests on adjacent frame rate pairs. Significance: *** p<0.001, ** p<0.01, * p<0.05, - = not significant.

Pair (f/s)	Mean Diff	t	df	p	Cohen's d	Sig.
			Score			
7 vs. 15	+690.6	-5.87	173.3	<0.001	0.88	***
15 vs. 30	+449.3	-3.66	170.6	<0.001	0.55	***
30 vs. 45	+242.2	-1.93	172.5	0.055	-	-
45 vs. 60	+29.9	-0.25	174.0	0.802	-	-
60 vs. 75	+14.1	-0.11	173.0	0.909	-	-
75 vs. 90	-56.0	+0.46	172.9	0.648	-	-
90 vs. 120	+81.1	-0.70	173.8	0.483	-	-
120 vs. 165	-57.3	+0.48	172.8	0.630	-	-
165 vs. 240	+30.0	-0.24	174.0	0.810	-	-
240 vs. 360	+20.0	-0.16	174.0	0.873	-	-
360 vs. 500	-18.4	+0.14	173.1	0.888	-	-
			Accuracy (%)			
7 vs. 15	+10.85	-6.59	164.5	<0.001	0.99	***
15 vs. 30	+2.74	-1.39	171.0	0.167	-	-
30 vs. 45	+1.84	-0.91	173.2	0.366	-	-
45 vs. 60	-0.81	+0.42	173.9	0.677	-	-
60 vs. 75	+0.00	-0.00	173.9	1.000	-	-
75 vs. 90	+0.28	-0.14	173.9	0.887	-	-
90 vs. 120	+0.72	-0.38	173.9	0.705	-	-
120 vs. 165	-0.72	+0.37	173.4	0.712	-	-
165 vs. 240	+0.31	-0.16	173.9	0.874	-	-
240 vs. 360	-0.70	+0.36	174.0	0.719	-	-
360 vs. 500	-0.51	+0.26	174.0	0.793	-	-
			QoE (low 1–5 high)			
7 vs. 15	+0.75	-9.77	117.0	<0.001	1.47	***
15 vs. 30	+0.85	-7.16	160.8	<0.001	1.08	***
30 vs. 45	+0.71	-5.10	173.6	<0.001	0.77	***
45 vs. 60	+0.35	-2.59	172.0	0.010	0.39	*
60 vs. 75	+0.35	-3.00	165.7	0.003	0.45	**
75 vs. 90	+0.08	-0.81	172.4	0.419	-	-
90 vs. 120	+0.07	-0.82	171.4	0.411	-	-
120 vs. 165	+0.00	-0.01	171.4	0.990	-	-
165 vs. 240	+0.04	-0.44	173.8	0.663	-	-
240 vs. 360	+0.01	-0.07	173.5	0.942	-	-
360 vs. 500	+0.04	-0.44	174.0	0.664	-	-

only 7 vs. 15 f/s as significant. In contrast, QoE improvements are statistically significant through five consecutive transitions, up to 60 vs. 75 f/s, and flattens above that. In short, performance saturates by about 30 f/s while perceived smoothness shows statistically meaningful gains through about 75 f/s. With 11 comparisons per metric, a Bonferroni correction ($\alpha \approx 0.0045$) only drops the 45 vs. 60 f/s QoE result, while the rest still stand.

While the difference in mean QoE smoothness values do not reach statistical significance for frame rates above 75 f/s, the observed, steady trend in mean QoE values suggests a meaningful improvement in player experience that warrants further investigation with a larger sample size.

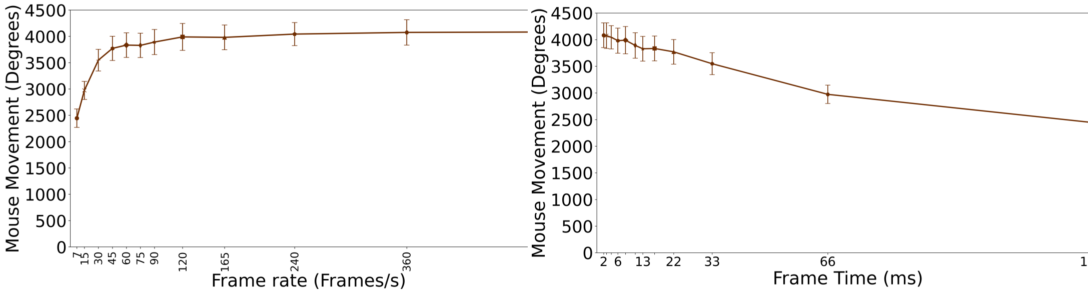


Fig. 8. Player actions (total mouse movement, in degrees of camera rotation per round) versus frame rate (left) and frame time (right). Each point is the mean across all rounds at that frame rate, and error bars are 95% confidence intervals. Mouse movement increases with frame rate and continues to climb slightly even at the highest frame rates (90–500 f/s), unlike score, which plateaus by 60 f/s.

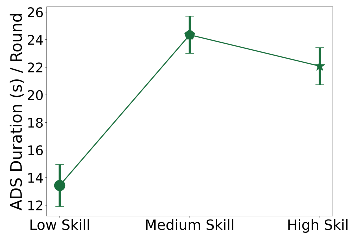
4.5 Player Behavior

This subsection analyzes the effects of frame rate on player behavior, here focusing on mouse movements. Figure 8 shows an analysis of the mouse movements, computed as the total degrees moved averaged across all users and all rounds with 95% confidence intervals, plotted versus frame rate (graph on the left) and frame time (graph on the right). The trends in mouse movements follow the trends in performance, with an increase in mouse movements as frame rates increase (and corresponding decrease in mouse movements as frame times increase) the difference in mouse movements for low frame rates compared to high frame rates is not as large as the corresponding differences in scores. This suggests players are trying to do about the same actions (moving the mouse the same distance to center the target in the reticle) across all frame rates, but with the previous performance data (Figure 6) showing the impact that frame rates have on performance. From the graph on the right of Figure 8, there is a slight upward trend in mouse movements even as frame rates go from 90 f/s to 500 f/s (corresponding to a slight decrease on the left edge of the graph on the right), suggesting the higher frame rates incentivizes more mouse movements. In addition, the trendline in the graph on the right shows a nearly linear relationship across the full range of frame times – 2 ms to 143 ms – suggesting player behaviors (actions) have not saturated at lower frame rates (e.g., 90 f/s) even if performance may have (e.g., score in Figure 6). Note, while there could have been an increase in mouse movement values recorded due to mechanical "noise" in readings from the mouse (i.e., small variations in readings even if the mouse does not move) that accumulate more at higher frame rates, this was not the case here – repeated readings of a still mouse at 500 f/s found all readings to be zero.

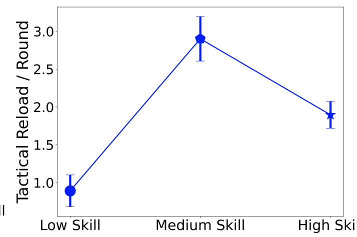
Observation of participants gameplay suggests that different skill levels mean different amounts of actions. For example, high skill players use the aim down sight (ADS) feature for more accurate shooting. We categorized players based on their average score across the entire session as a proxy for skill, grouping them into three categories – high skill, medium skill and low skill.

Figure 9 show aggregates of 3 metrics, showing how players with different skill levels played in different ways. Figure 9a shows how players with different skill levels use the ADS feature of the weapon. The graph indicates that low-skill players use ADS less than medium- or high-skill players. However, medium-skill players might be overusing ADS compared to hip-firing (i.e., not using ADS), hence scoring lower, while high-skill players seem to find a balance between the two.

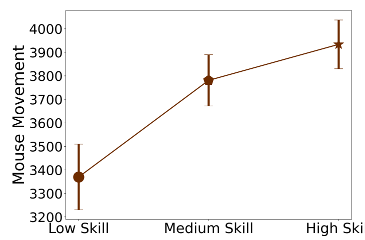
Figure 9b shows the tactical reload count, where players deliberately press the reload button before their weapon runs out of ammo. Doing so at the right time allows players to obtain a full



(a) Aim down sight (ADS) duration per round.



(b) Tactical reload count per round.



(c) Total mouse movement (degrees) per round.

Fig. 9. Player action differences by skill level. Players were grouped into low, medium, and high skill based on average session score. Each point is the mean of the metric across players in that skill group and error bars are 95% confidence intervals. (a) ADS duration per round (seconds), (b) tactical reload count per round, (c) total mouse movement per round (degrees of camera rotation). Across all three metrics, medium-skill players tend to overuse ADS and tactical reloads relative to high-skill players.

magazine of bullets before first encountering an opponent, avoiding costly reload time during battle. Similar to the trend in Figure 9a, low-skill players use tactical reloads less frequently, medium-skill players tend to overuse it, and high-skill players find a better balance.

We conjecture that in an FPS game, such as Lead Rush, how readily a player discerns the frame rate – low or high – is largely impacted by the movement of their mouse. The more a player moves the mouse, the more the first-person perspective camera moves and the more likely a player notices the frame rate – whether choppy for a low frame rate (e.g., 7 f/s) or smooth for a high frame rate (e.g., 500 f/s).

To test this, Figure 10 shows the correlation between perceived smoothness and mouse movement. The y-axes are the QoE scores and the x-axes are the total mouse movements (in degrees) in a round. Mouse movement is measured in degrees of in-game camera rotation accumulated over the round – since Lead Rush is a first-person game, moving the mouse rotates the camera, so larger values mean the player looked around more during the round. Each point is the average for 10 equal clusters of mouse movements. The extremes are shown – the left graph has values for 7 f/s and the right graph has values for 500 f/s. The lines are linear trends with the coefficient of determination (R^2) shown.

At 7 f/s (left), the trend line shows a negative slope, suggesting that as players moved the mouse more, they became more aware of the choppiness, resulting in lower QoE. Conversely, at 500 f/s (right), the trend line is positive, indicating that players that moved the mouse more perceived more smoothness, resulting in a higher QoE.

We do the same analysis for all frame rates and compute the slopes (QoE versus mouse movement) for the trendlines. Figure 11 shows these slopes with the y-axis the slope – QoE change per 10k

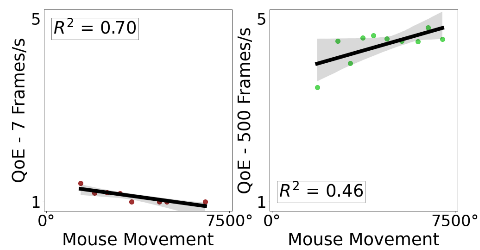


Fig. 10. Correlation of QoE with total mouse movement per round at 7 f/s (left) and 500 f/s (right). Each point is the mean QoE for one of 10 equal-size bins of mouse movement (in degrees of camera rotation); lines are linear fits with coefficient of determination (R^2).

degrees of mouse movement. The slopes follow the expected relationship – low frame rates have a negative slope meaning moving the mouse more reveals the choppiness, while as frame rates get ultra high, moving the mouse more allows players to perceive more smoothness. Each slope is fit from 88 per-round observations (44 players × 2 rounds) at that frame rate, binned by mouse movement into 10 equal-width bins before the linear fit, as in Figure 10. Slope magnitudes swing across frame rates because QoE is near-saturated at mid frame rates – when most rounds get a 4–5 regardless of mouse movement, the fit has little y-axis range to work with and small shifts in the bin means produce large changes in slope.

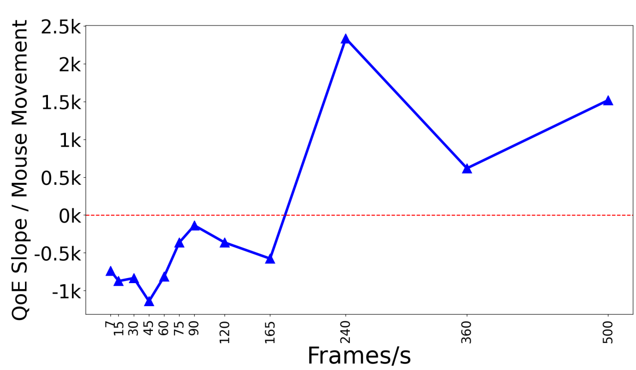


Fig. 11. Slope of QoE versus total mouse movement, by frame rate. Each point is the slope of a per-frame-rate linear fit (as in Figure 10), expressed as QoE change with respect to mouse movement.

The slope, intercept, and R^2 values for the correlation between QoE and mouse movement varied across frame rates, with differences observed at 240 and 500 f/s. Higher skill players had greater total mouse movement compared to lower skill players, indicating that frame rates may affect skilled players differently.

5 COMPARISON WITH OTHER WORK

Our study extends a body of work that has examined how frame rates affect game players under tightly controlled tasks. While our work focuses on FPS actions, prior studies have focused on a range of player actions, from shooting human-like bots in an FPS game (similar to our study), to keyboard-only shooting in a third-person target selection game, to mouse-based target selection, to controller-based target intersection in virtual reality (VR). These earlier studies use a similar methodology – isolating a specific player action within a game, designing a user study that controls the frame rate while measuring the impact on players, and analyzing the results via graphs of frame rate as the independent variable (x-axis) and the impact the dependent variable (y-axis). These similarities are the basis for comparison with the trends observed and our results.

Table 3 provides a summary of the relevant studies. The first column is the citation, the second the study's first author, the third the game participants played in the user study, the fourth the number of participants, the fifth the dominant player action, the sixth the player input hardware, the seventh the main player performance metric, the eighth the main player experience metric (if any), and the ninth the frame rates tested.

To enable direct comparisons, we reconstructed each study's result curves using numeric values taken from graphs published in their papers. Screenshots of the original figures were taken from the papers and given to a large language model [13] to extract approximate data points, manually verified to check that the values were accurate. In order to allow comparison of performance across different tasks, game scores were normalized relative to scores at the lowest common frame rates, with completion times inverted so that higher values mean better performance. Player experience (QoE, playability) remain on their original (low) 1 to 5 (high) scales. All converted data points were then replotted with the matching portion of our user study data.

5.1 Methodologies

Claypool – Quake 3 Arena: Claypool and Claypool studied shooting performance in Quake 3 Arena using a customized shooting map [2]. The map had two facing platforms separated by a gap so that the human player and a single bot could not cross over. The bot's platform had no cover except a small wall at the spawn point, and the player's platform only had back and side walls to prevent accidental falls. The only weapon for both player and bot was a Railgun, which is a one-hit kill on the level-1 bot and a 2 second firing delay. There were no other weapons or items. Frame rate was controlled via a test harness that started Quake 3 with specific settings. Five frame rates were tested: 3, 7, 15, 30, and 60 f/s, each combined with three resolutions (320×240, 512×384, and 640×480 px). For each condition, the client ran a 30 second game against the bot, then terminated the process and loaded the next configuration in random order. A server recorded kills and deaths for each 30 second run. Player performance for shooting was taken as the number of times the player killed the bot in the round. For our analysis, we chose the score and playability graph versus frame rate from their study.

Claypool – Custom Shooter: Claypool and Claypool used a custom-built game to test how frame rate and resolution affect two actions: navigating and shooting [3]. The study covered three perspectives: first-person, third-person linear, and third-person isometric, with the same game played with the different camera perspectives. Each perspective had its own shooting level. In every shooting level, the user controlled an avatar and fired at a moving enemy that bounces off walls. The player fired using the spacebar with a fixed 500 ms delay between shots. Player performance was defined as score = hits × (hits / shots taken). Each session lasted 15 seconds. A test harness cycled through frame rates of 7, 15, and 30 f/s and resolutions of 800×600 and 1280×1024 px. Their study had 36 total sessions per user, randomizing perspective, action, frame rate, and resolution. For our analysis, we chose the first person perspective – score and playability versus frame rate from their study.

Janzen – Target Selection: Janzen and Teather studied how frame rate and latency affected moving target selection [7]. Participants used a mouse to click moving targets under different combinations of frame rate and added latency. Each target was a 100×100 px square that moved at a fixed speed and bounced when hitting screen edges. When a target was clicked, it briefly changed color and a new target appeared 300 pixels away. Input latency was simulated by delaying

Table 3. Summary of prior frame rate studies (restricted tasks).

	Study	Game	Users	Task	Input	Performance metric	Experience metric	Tested frame rates (f/s)
[2]	Claypool	Quake 3 Arena	60	Shooting bots	Mouse + keyboard	Score	Playability (1–5)	3, 7, 15, 30, 60
[3]	Claypool	Custom Shooter	27	Shooting targets	Keyboard	Score	Playability (1–5)	7, 15, 30
[7]	Janzen	Target Selection	11	Clicking moving targets	Mouse	Targets clicked	–	15, 30, 45, 60
[15]	Spjut	FPSci	8	One-hit shooting	Mouse + keyboard	Task completion time	–	60, 120, 240, 360
[21]	Wang	Fruit Cutting	32	Slicing fruit	Vive controllers	Accuracy	–	60, 90, 120, 180
	Tokey	Lead Rush	44	Shooting target	Mouse + keyboard	Score, accuracy	Smoothness (1–5)	7, 15, 30, 45, 60, 75, 90, 120, 165, 240, 360, 500

both pointer motion and click events. The study tested four frame rates: 15, 30, 45, and 60 f/s, and three latency levels (0, 50, 100 ms) added on top of a baseline system latency. Each condition lasted 20 seconds within an 80-second trial, and all conditions were counterbalanced. The main player performance metric was number of targets clicked. For our analysis, we chose the 0 latency level as it most closely matched our methodology.

Spjut – FPSci: Spjut et al. studied how frame refresh rate and latency affected first-person targeting tasks using their custom application *FPSci* [15]. The study included two task types: a 1-hit task and a tracking task. The 1-hit task spawned a target at a random location; the user attempted to align the crosshair and click to destroy the target, with a 0.5 second refire delay and up to ten shots in a 5-second trial. The test harness cycled through five motion types: Static, Straight, Stray-Easy, Stray-Hard, and Jump and four refresh rates: 60, 120, 240, 360 f/s. Latency was controlled independently using three latency settings (low, mid, high) by injecting delay. All participants were skilled FPS players. Performance was measured using task completion time. For our analysis, we chose the 1-hit straight low-latency task as it is most similar to our task.

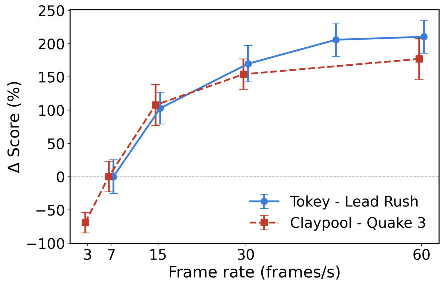
Wang – Fruit-Cutting: Wang et al. used two controlled VR applications to study how frame rate affects performance, user experience, and simulator sickness [21]. We focused on Application 1, a Fruit Cutting Task inspired by the game Fruit Ninja. Participants wore a Pimax 5K Super HMD and used Vive controllers as virtual swords to cut fruits moving through a cubic cutting area. Fruits spawned at fixed distances and moved at one of four speeds (10, 20, 30, 40 m/s). Thirty-two participants completed trials under four frame-rate conditions: 60, 90, 120, and 180 f/s. For each frame rate and speed, accuracy (fraction of fruits cut) and timing measures were logged, and participant responses were collected after each block. For our analysis we chose the accuracy versus frame rate plot for the fruit cutting task.

5.2 Player Performance

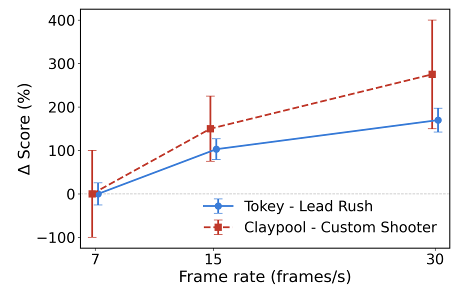
To compare player performance across studies where each study had a slightly different metric, we analyze *percentage change* in shooting or targeting performance as frame rate varies. Each subplot in Figure 12 corresponds to one prior work (shown in red) and its comparison with our study, Lead Rush (shown in blue).

Figure 12a shows Quake 3 shooting scores alongside Lead Rush scores, both expressed as percentage change relative to 7 f/s. In both datasets, score increases as frame rate increases, with gains from 7 to 15 f/s and 15 to 30 f/s and a smaller difference between 30 and 60 f/s. Over this shared range, the Claypool-Quake 3 study aligns with our Lead Rush results – low frame rates reduce shooting performance and that most improvements to player performance occur by about 30 f/s.

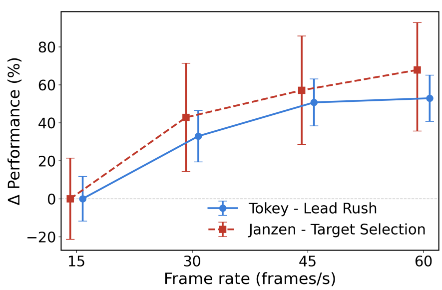
Figure 12b compares first-person shooting scores from Claypool-Custom Shooter with Lead Rush, both expressed as percent change relative to 7 f/s. This Claypool study also aligns with our Lead Rush results as scores rise consistently from 7 to 15 f/s and 15 to 30 f/s in both games.



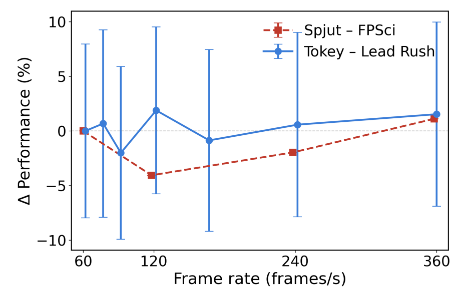
(a) Claypool–Quake 3 Arena.



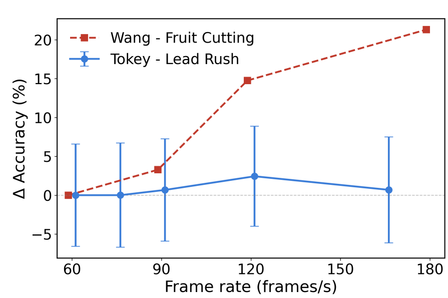
(b) Claypool–Custom Shooter.



(c) Janzen–Target Selection.



(d) Spjut–FPSci.

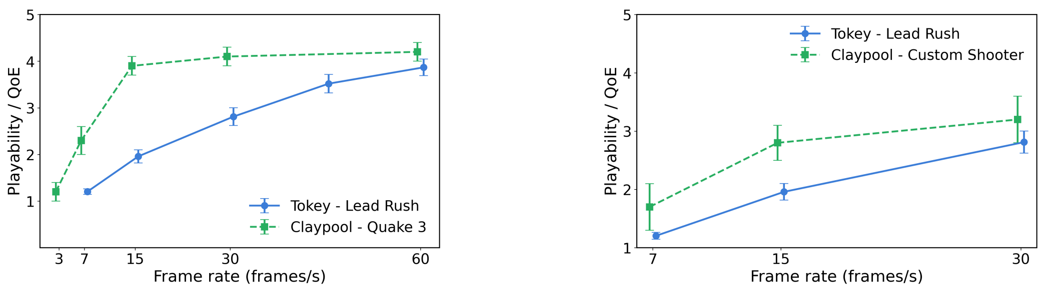


(e) Wang–Fruit-Cutting.

Fig. 12. Player performance comparisons between prior work and Lead Rush. Each subplot shows percentage change in performance relative to the study's baseline frame rate (the lowest common frame rate for each comparison). Each point is the mean across all participants and rounds, and error bars are 95% confidence intervals. Performance metrics vary by study (Score for Claypool–Quake 3 and Claypool–Custom Shooter, targets clicked for Janzen, task completion time for Spjut, accuracy for Wang), all normalized and aligned so that higher values indicate better performance.

Figure 12c compares Janzen's moving target selection results (0 ms latency condition) with Lead Rush scores, both expressed relative to 15 f/s. Here as well, Janzen's results align well with our Lead Rush results – values increase similarly from 15 to 30 f/s, 30 to 45 f/s, and 45 and 60 f/s in both datasets, showing similar upward trends across this frame rate range.

Figure 12d shows Spjut et al.'s FPSci 1-hit Straight low-latency condition and Lead Rush (both normalized to 60 f/s). Spjut's results also reinforce our Lead Rush results, albeit their results



(a) Claypool–Quake 3 Arena.

(b) Claypool–Custom Shooter.

Fig. 13. Experience comparisons across prior work and Lead Rush, both rated on a 1–5 scale (Lead Rush: smoothness, 1 = Very Choppy to 5 = Very Smooth; Claypool studies: playability 1 = low to 5 = high). Each point is the mean across all participants and rounds at that frame rate, and error bars are 95% confidence intervals.

have much larger confidence intervals likely due to fewer users in their study. In both datasets, performance stays nearly flat as frame rates rise from 60 to 360 f/s, with only minor fluctuations.

Figure 12e compares accuracy from Wang et al.'s VR Fruit Cutting task with Lead Rush shooting accuracy, both expressed relative to 60 f/s. For this study, the results diverge with Wang's fruit-cutting showing a clear upward trend with frame rate, while Lead Rush remains mostly flat, reflecting differences between VR slicing motions and mouse-based aiming. As a possible explanation for this difference, a head-mounted display covers the user's full field of view, including the periphery which is more sensitive to motion and flicker than the fovea [20]. VR also adds head-tracking latency that PC monitor setups do not have, which is partly why typical VR frame rate floors are 90 f/s versus 60 f/s for monitors. A controlled study comparing VR and monitor versions of the same task could be future work to confirm.

5.3 Player Experience

Only two of the prior studies assessed participant subjective experience: Claypool–Quake 3 (playability) and Claypool–Custom Shooter (playability). Figure 13 compares their results with Lead Rush smoothness ratings.

After each 30-second shooting run, users in the Quake 3 study rated the playability given the prompt "Rate the playability of this game session." Figure 13a compares these playability ratings with smoothness scores from Lead Rush over the shared 3–60 f/s range. Both datasets show low ratings at 7 f/s, a clear rise between 7 and 15 f/s, and smaller changes from 30 to 60 f/s. However, the Claypool-Quake 3 study shows playability has a sharper rise, reaching near the maximum at only 15 f/s whereas the Lead Rush rise is more gradual, closer to linear over the same range.

In the Custom Shooter study, users rated session playability after each 15-second trial using the same five-point scale and the same prompt for playability. Figure 13b compares these playability scores with Lead Rush smoothness ratings over the shared 7–30 f/s range. Both datasets show higher ratings at 15 f/s than 7 f/s, and higher ratings at 30 f/s than 15 f/s, albeit the playability scores are slightly lower than the smoothness scores for the same frame rates.

5.4 Summary

This section makes an additional scientific contribution in answering the question: are results from previous experiments confirmed by our experiments? While our work is not a reproduction of any single prior study, it does allow us to make a comparison of results from studies that had similar methodologies. Such comparisons of results done by independent studies are valuable for generalizing findings beyond the experience of any individual experiment. Our comparative analysis confirms that performance results degrade similarly across studies, albeit with a notable difference in a VR task. Likewise, trends in player experience also align, although the trends may depend upon the specific questions asked of participants. Together, these comparisons provide for a stronger confirmation of trends than the results individually.

6 LIMITATIONS

Our study is designed to achieve consistent, fixed frame rates in order to assess the effects of frame rate precisely. In practice, for many games and game systems, the frame rates fluctuate over time due to factors such as system load, network conditions, and game-state complexity, which may alter the fixed frame rate effects in our study.

Our game was also deliberately focused on only the gameplay core to a FPS game – moving and shooting in combat with a single enemy. However, most commercial FPS games are more complex, with diverse mechanics, environments, and player interactions that can influence player performance and experience. Our study also only used a fully automatic rifle, while most FPS games offer weapons with different characteristics (e.g., firing rates, damage, bullet spread), giving players an opportunity to adjust their strategies with frame rate. More precise weapons (e.g., sniper rifles) may be more sensitive to lower frame rates and, possibly, may benefit more from higher frame rates.

Our study relied upon users providing truthful responses to a smoothness question after only one minute of gameplay, before the frame rate switches in the next round. That was deemed long enough in our pilot tests, but in actual games, users may become acclimated to a given frame rate when playing for a longer time, possibly adjusting the QoE scores up or down from those we record.

7 CONCLUSION

While frame rates with 60 f/s are common among PCs and similar devices, many gamers seek systems with higher frame rates – 120 f/s, 144 f/s, and even 240 f/s. This is especially true for players who push for technologies that improve their experience and provide a competitive edge. In particular, first-person shooter (FPS) game players often drive display and input-latency improvements given the prevalence of FPS titles in esports. Higher frame rates provide smoother visuals and lower input latencies, but likely have diminishing returns as technologies push the limits of human perception and performance.

This study explores the effects of frame rate on player experience, performance, and behavior using a bespoke FPS game, Lead Rush, designed to provide consistent frame rates from a low of 7 f/s to an ultra-high 500 f/s. A total of 44 participants each played 24 one-minute rounds of Lead Rush across 12 different frame rates, with objective data collected on performance (e.g., score) and subjective data gathered on perceived smoothness.

Our study results show that increasing frame rates does help player performance up to a point – specifically, performance at low frame rates can be markedly improved by increasing the frame rate. Player performance rises sharply from 7 f/s through 90 f/s, but sees little benefit for frame rates higher than 120 f/s, suggesting diminishing returns for performance once latency becomes extremely low. However, even without clear performance gains, frame rates above 90 f/s do seem to improve player experience, with our data show a slight upward trend in mean smoothness ratings all the way to 500 f/s. Perception of low and high frame rates is likely enhanced by more frequent mouse movements, with higher-skilled players moving the mouse more than lower-skilled players.

We also compared our results with prior work that studied the impacts of frame rate across several controlled game tasks, including commercial FPS shooting, keyboard-only targeting, mouse-based selection, latency-normalized shooting, and VR interaction. Across overlapping frame-rate ranges, our results confirm patterns demonstrated in previous works, particularly in the 7–90 f/s region where most prior data exists. This comparative analysis strengthens the scientific contribution more than the individual studies alone.

Future research could examine how ultra-high frame rates affect other genres that rely on precise timing –such as racing, rhythm, or fighting games – to better understand impacts on player experience and performance. Display size and resolution may also confound the effects of frame rate, so studies using both larger, higher-resolution monitors and smaller, lower-resolution displays could be worthwhile.

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