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Game Player Response Times versus Task Dexterity and Decision Complexity

by

Chunzhen Jiang
Aritra Kundu
and Mark Claypool

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WORCESTER POLYTECHNIC INSTITUTE

Computer Science Department
100 Institute Road, Worcester, Massachusetts 01609-2280

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Chunzhen Jiang, Aritra Kundu, and Mark Claypool
cjiang4,akundu,claypool@wpi.edu
Worcester Polytechnic Institute
Worcester, MA

ABSTRACT

The popularity of games means people that play games may have different performance for basic reaction and decision making tasks in comparison to people that do not play games. This paper presents results from two user studies that evaluate self-rated gamer ability for a reaction-time task, a task with varying decision complexities and a task with varying dexterity requirements. Analysis of data from over 150 users shows small effects of self-rated gamer skill on task, but substantial effect of the decision parameters (choices) and dexterity parameters (size and distance) on performance.

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1 INTRODUCTION

Computer games are the world's most popular form of entertainment, with global sales increasing at an annual rate of 10% or more [13]. Moreover, the impacts of gaming are not only fiscal, as fast-paced computer gaming has been shown to improve rapid-response decision making [5], with gamers able to respond to visual stimuli faster than non-gamers [7]. Our past research has shown self-rating of gamer ability correlates with actual performance for some game-specific tasks [1, 15].

What has not been explored is how self-rating of gamer ability correlates with performance along different dimensions of interaction required of gamers during play. In particular, we are interested in how self-rated gamer ability predicts task performance along two dimension: dexterity and decision complexity. For task dexterity, we evaluate self-rated gamer ability in regards to Fitts' Law, which governs the time to select a target based on the size and distance. For decision complexity, we evaluate how self-rated gamer ability impacts a rapid-response task with different numbers of choices.

For evaluation, we design and conduct two users studies deployed via Javascript through a web browser. Both studies measure participants' reaction times. The decision complexity study has participants respond as fast as possible to visual stimuli with 1, 2 or 3 choices. The dexterity study has participants select circles of different sizes and distances as quickly as possible.

Analysis of data from over 150 participants shows a modest improvement in reaction time versus gamer ability – about a 350 milliseconds mean for low skill players versus about a 325 millisecond mean for high skill players. These same trends hold at all three levels of decision complexity. Adding a second choice increases response times by about 50% over a single choice reaction time test, and having three choices approximately doubles the response time over a reaction time test. Low and medium skill players have a similar linear fit for response time versus index of difficulty in Fitts' Law, but high skill players have a lower y-intercept, indicating faster response times.

The rest of this report is organized as follows: Section 2 describes work related to this paper, Section 3 describes our methodology, Section 4 presents the results, and Section 5 summarizes our conclusions and presents possible future work.

2 RELATED WORK

This section describes related work in two main areas: studies of reaction time for gamers (Section 2) and Fitts' law describing predicted performance for target selection (Section 2).

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Gamers and Reaction Time

Reference.com describes some prior studies that measured human reaction times [12]. Most notably: 1) humans respond more quickly to sound than sight, 2) the stronger the stimuli, the faster the response, 3) the more cognition required, the slower the reaction, and 4) response times measured via computer are about 50 ms slower.)

A case study [2] with a few elite eSports gamers shows their reaction times vary from a low of 170 ms up to about 300 ms.

Richardson et al. [14] conduct a user stuy with 90 people and find the mean reaction time for gamers (defined as playing 4+ hours per week) to be about about 300 ms, while non-gamers were are about 350 ms.

Tonnessen et al. [17] examined the reaction times for elite sprinters using video feeds from cameras mounted on the starting blocks. Generally, they found those with faster reaction times were faster sprinters; the finalists had reaction times of about 150ms.

Dye et al. [3] compare reaction times for gamers versus non-gamers by comparing results from previous studies in a sort of meta-study. Overall, they find gamers have slightly better reaction times. Moreover, they have a graph that seems to suggest that tasks that require more "thinking" tend to have a higher response time and that "experts" (e.g., experienced game players) may have lower reaction times. Our work confirms and validates these ideas.

Green et al. [5] found that fast action games, such as First Person Shooters, can improve the response time for simple auditory or visual questions. Non-gamers subjected to 50 hours of FPS gameplay were up to 25% faster answering such questions than non-gamers subjected to 50 hours of a slower-paced game, without any more mistakes.

More fundamentally, Latham et al. [7] found that expert video game players have faster neural processing of visual stimuli than non-video game players, with reaction times about 290 ms for the non-gamers and about 275 for the gamers.

Table 1 summarizes the findings from previous work on reaction times for gamers. Elite athletes have reaction times of about 150 ms, and elite gamers are probably close to, if slightly above, that. Good gamers are probably about 250 ms, and average gamers about 300 ms. Non-gamers average about 350 ms.

Gamers and Fitts' Law

Paul Fitts pioneered early seminal work in the area of human-computer interaction and ergonomics in the form of creating *Fitts' Law* [4]. *Fitts' law* describes the time (T) to select a stationary target based on an index of difficulty (ID):

Table 1: Summary of typical reaction times.

Group	Reaction Time	Ref.
Human minimum	109 ms	[12]
Elite athlete	150 ms	[17]
Elite gamer	150-200 ms	[2]
Good gamer	250 ms	[7]
Average gamer	300 ms	[14]
Non-gamer	350 ms	[14]

$$T = k_1 + k_2 \cdot ID \qquad (1)$$

where k_1 and k_2 are constants specific to the user group and task at hand. The index of difficulty (ID) is proportional to: 1) the gap distance (D) from the source to the target, and 2) the width of the target (W):

$$ID = \log_2\left(\frac{2D}{W}\right) \qquad (2)$$

While Fitts developed and validated his law based on hand movements with a stylus, Fitts' Law has been shown to be applicable to a variety of other conditions (e.g., underwater [6]) and input devices (e.g., eye tracking [18]). Since many modern uses of Fitts' Law are for computer devices with two dimensional displays, MacKenzie and Buxton's [10, 16] investigation of Fitts' Law provided guidelines for use of the law in evaluating pointing devices.

Fitts' Law has been applied to games, too. Ramcharitar and Teather [11] assess Fitts' law comparing a mouse to three different game controllers: a thumb-based touchpad, a thumbstick, and a gyrosensor. Lee et al. [8] Develop a prescriptive model of frequently used operations in mobile games - tapping, pointing, dragging, and flicking = within the purview of Fitts' law. Looser et al. [9] evaluate whether or not a First Person Shooter, where the player pans the camera in the game world to center the target in the reticle, is accurately modelled by Fitts' Law. Results from an 11 person user study show excellent Fitts' modelling, with metrics similar to traditional pointing.

3 METHODOLOGY

To assess the gamer reaction times for tasks with different decision complexities and task dexterity difficulty, we conducted two different user studies: Section 3 describes our study of reaction time versus decision complexity and Section 3 describes our study of reaction time versus task dexterity.

Given the onset of COVID-19 and the difficulty in doing in-person user studies, both users studies deploy tasks via Javascript applications run through a Web browser. While absolute reaction times are difficult to assess through a web interface, especially when run on a myriad of client platforms, our intent is to compare the relative performance for different tasks and compare the relative performance for gamers with different self-rated skills.

Both user studies followed the same procedure:

- Users answered some demographic questions: age, gender, and self-rating as a gamer.
- Users used a computer (with mouse) to navigate to our web page with our Javascript applications.
- Users did a small set of tasks.
- Users copied the task results into our survey.

User participation was voluntary and approved by the Institutional Review Board (IRB). Participants were solicited through campus mailing lists and the authors' online communities and social networks (e.g., Facebook, Weibo).

Decision Complexity

We developed a Javascript application that had users react to input with a keyboard press. Users click the "Ready" button above a white box to start the test. The box changes color from white to green in a random interval of time from 0.05 to 3 seconds. When the box changes to green, the user must press the Z button on the keyboard as quickly as possible. The time from when the box changes color until the user presses Z is recorded as the reaction time. This cycle is repeated 5 times. Anytime the user presses Z after "Ready' but before the box changes color the user is required to re-do the task.

Figure 1 depicts a screen shot of the task after first successful test, but before Z is pressed a second time.

Task 2 is the same as task 1 except that instead of 1 choice, the user has 2. If the white box changes color to green, the user still presses Z. However, if the white box changes to yellow, the user must press X.

Task 3 is the same as task 2, but with 3 choices - If the white box changes color to green, the user presses Z, if yellow, press X, and if blue, press C.

The order that the 3 tasks are presented is random.

For tasks 2 and 3, mistakes (i.e., pressing the wrong key) are recorded as "Wrong". Users are allowed up to 3 mistakes, but otherwise need completed the task successfully 5 times. After 5 successful rounds, the responses are displayed on the screen so the participants can copy and paste the data onto the survey for our later analysis.

For the first task, after clicking the "Ready" button, the function `appearAfterDelay()` is called to make the shape appear (via `makeShapeAppear`) or provide a popup alert to prompt the user to copy their data to the survey. The final condition has the user repeat the test if the button is pressed too early. The code for tasks 2 and 3 are similar, except the code also determines if the correct key was pressed - Z, X or C - depending upon the color.

Figure 1: Screen shot of decision task 1.

```
function appearAfterDelay()
{
    if(clicktimes<5)
    {
        setTimeout(makeShapeAppear,Math.random()*3000);
    }
    else if(clicktimes==5)
    {
        setTimeout(makeShapeDisappear,3000);
        clickornot=false;
        alert("Please copy the data, hit the back button on your browser, and paste into the survey.");
        document.getElementById("after").innerHTML="Copy the data below:";
        suggestiondisappear();
    }
    else
    {
        setTimeout(makeShapeDisappear,3000);
        clickornot=false;
        document.getElementById("centralbutton").style.display="";
    }

}
```

Figure 2: Sample code for Descision Complexity Task

Task Dexterity

The demographic questionnaire instructs the user to use a mouse and to play in full-screen mode. Users were also asked the display size of their desktop monitor or laptop.

We developed a Javascript application that had users react to input with a mouse click. After indicating they were ready by clicking a button, the screen changes color after a random time interval between XXX and YYY seconds. The user subsequently clicks the mouse as quickly as possible. If the user clicks before the screen changes color, an alert warning is displayed and that outcome is ignored. After 5 successful rounds, the responses are displayed on the screen

Figure 3: Screenshot of dexterity task.

so participants can copy and paste the response data onto the survey for analysis.

We developed another Javascript application where users click on a button indicating they are ready, thus centering the mouse on the screen. After a short amount of time (between 0 and 2 seconds), a circle chosen randomly from one of two sizes appears a random distance from the center of the screen. The user subsequently clicks on the circle as fast as possible. After 5 successful rounds, the responses are displayed on the screen so the participants can copy and paste the data onto the survey for our later analysis.

Figure 3 depicts a screen shot of the task showing a randomly placed circle the user must click on as fast as possible with the mouse.

Clicking on the ready button would invoke `makeShapesAppear()` as shown in Figure 4 to display a circle of a particular size at a random location on the screen. The circles were displayed at 50 or 100 pixels in diameter. The difficulty of the task depends upon the circle size and the distance from the mouse at the center of the screen.

```
function makeShapeAppear() {

        var top =Math.random() * (h/2);

        var left = Math.random() * (w/2);

        var width = Math.random() * 1000;
        arrt.push(top.toFixed(2));
        arrl.push(left.toFixed(2));

        if(count%2==0)
            {document.getElementById("shape").style.width = 100 + "px";
             document.getElementById("shape").style.height = 100 + "px";

            }
          else {
               document.getElementById("shape").style.width = 50 + "px";
             document.getElementById("shape").style.height =  50 + "px";

             }

        document.getElementById("shape").style.backgroundColor = getRandomColor();

        document.getElementById("shape").style.top = (top) + "px";

        document.getElementById("shape").style.left = (left) + "px";


        document.getElementById("shape").style.display = "block";

        start = new Date().getTime();

    }
```

Figure 4: Sample code for Dexterity Task

Since the main goal of our analysis is to ascertain performance versus self-rated gamer ability, we provide more analysis of this attribute. Table 3 shows the breakdown of self-rated gamer ability for each user study, with the mean and standard deviation reported by $\bar{x}$ and s in the last two columns. The bottom row shows the breakdown of both studies combined into one. Both studies have a slight skew towards higher self-rated skill (mean self-rated skill is slightly above 3 and the mode 4 for each dataset) but there are players of all self-rated skill levels in each.

Table 3: Breakdown of self-rated skill

	Self-rated skill						
Study	1	2	3	4	5	$\bar{x}$	s
Decision	3	8	21	19	15	13.2	7.56
Dexterity	2	6	21	35	24	17.6	13.5
Total	5	14	42	54	39	30.8	20.4

4 RESULTS

Our decision complexity user study had 66 participants and our task dexterity user study had 88 participants. Table 2 summarizes the main demographics from both studies. The columns are: "N" - number of participants, "Age" - average age with standard deviation in parentheses, "Gender" - gender breakdown for male, female and not specified, and "Gamer" - the self-rated gamer score (1-low to 5-high) with the standard deviation in parentheses.

Table 2: Demographic summary.

Study	N	Age	Gender	Gamer
Decision	66	23.6 (8.7)	49 ♂ 14 ♀ 1 ?	3.6 (1.1)
Dexterity	88	20.9 (4.0)	66 ♂ 20 ♀ 2 ?	3.8 (1.0)
Total	154	22.1 (6.6)	115 ♂ 34 ♀ 3 ?	3.7 (1.0)

Reaction Time

Both of our user studies have a reaction time task where users respond as quickly as possible to a change in color on the screen. We combine the data from both tests and analyze the relationship between self-rated skill as a gamer and reaction time. Based on earlier work, we combine users in skill groups 1-2 and skill groups 4-5 to obtain 3 skill groups: low, medium and high.

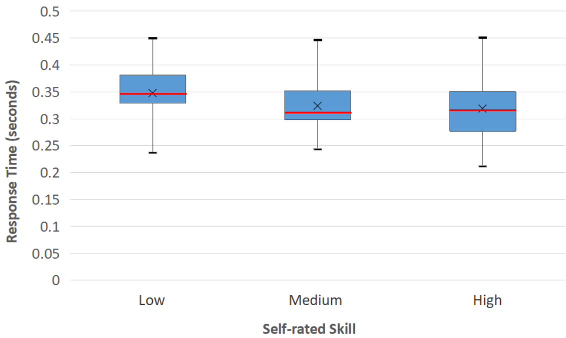


Figure 5: Reaction time. This is an EXAMPLE and needs to be replaced with the actual figure

Given the nature of the study, in some cases the user may not have been paying attention to the test, resulting in an unusually high response time. To account for this, we remove all points that are higher than $1.5 \times IQR$. In total, 20 points were removed.

Figure 5 depicts a boxplot of the results. The x-axis is the self-rated skill group and the vertical axis is the reaction time. The boxes denote the bottom and top quartiles, with the line in the middle the median and the cross is the mean. The whiskers are ...

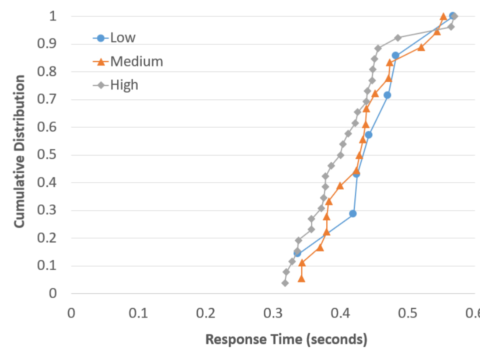
Table 4: T-test for Reaction Time task.

Comparison	t-Statistic	p value	d
Low - Med.	t(26) = 1.72	0.10	0.63
Med - High	t(48) = -0.07	0.95	0.02
Low - High	t(40) = 1.45	0.16	0.51

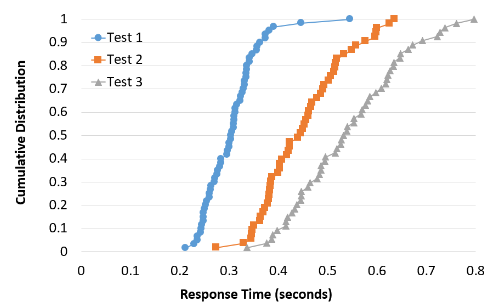
The Cohen's d effect sizes are 0.63, 0.02 and 0.51 for low-medium, medium-high and low-high respectively.

Decision Complexity

Figure 6 shows distributions of the response times for the decision complexity tasks. Figure 6a has the data grouped by different skill groups and Figure 6b has the data grouped by decision complexity task. For both graphs, the x-axis is the average response time in seconds and the y-axis is the cumulative distribution. Each point is the average response times for the users. From Figure 6a, there is slight separation in the distributions for the different skill groups, with the low skill group slightly higher (shifted to the right) than the medium skill group and the medium skill group slightly higher than the high skill group. The within-group variation appears larger than the between-group variation. From Figure 6b, there is a distinct separation in the distributions, with the task 1 group lower (shifted to the left) than the task 2 group and the task 2 group lower than the task 3 group. This difference is large given the within-group variation.



(a) Grouped by skill.



(b) Grouped by task.

Figure 6: Distribution of average response time for decision tasks.

Figure 7 graphs the response times for a task versus user self-rated skill. The x-axis is the self-rated skill and the y-axis is the response time. Each point is the response time averaged across all users for a given skill group and task, shown with a 90% confidence interval. From the figure, looking vertically there is a clear separation of confidence intervals at all skill levels for all tasks, with the higher decision complexity tasks taking more time on average than the lower complexity tasks. Looking horizontally, there is a visible downward trend (lower is better) in average response time with higher self-rated skill. However, there is overlap in the confidence intervals for each adjacent pair-wise comparisons.

T-test results ($\alpha = 0.1$) are shown in Table 5. The first column indicates the comparisons, with the top half of the table comparing self-rated skill groups and the bottom half comparing decision task groups. The last column is the effect size, Cohen's d. From the Table, differences in skill group are not significant, while differences in task decision complexity are for each pair, even using a Bonferroni correction.

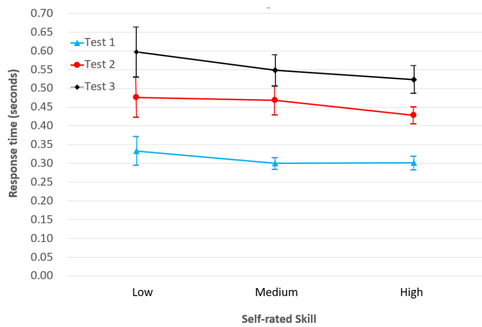


Figure 7: Average response time for decision tasks.

Table 5: T-test for decision complexity tasks.

Comparison	t-Statistic	p value	d
Low - Med.	t(23) = 0.6	0.55	0.28
Med - High	t(42) = 1.2	0.24	0.38
Low - High	t(31) = 1.5	0.15	0.64
Task 1 - Task 2	t(111)= -10.8	< .001	2.0
Task 2 - Task 3	t(105)= -5.0	< .001	2.8
Task 1 - Task 3	t(112)=-14.8	< .001	1.0

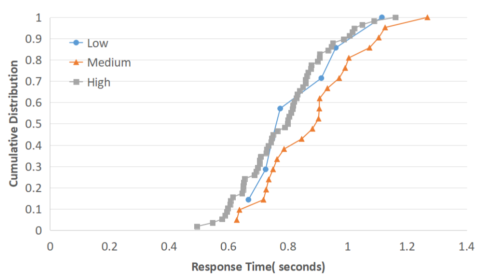


Figure 8: Distribution of average response time for dexterity task

Dexterity

Figure 8 graphs the cumulative distribution of the response times for the dexterity task with the user self rated skill. The x-axis is the self-rated skill and the y-axis is the response time. Each point is the response time averaged across all users for a given skill group and task, shown with a 90% confidence interval. From the graph, there is a slight separation for the medium skill players from the other distributions, but the low and the high skill distributions overlap. The horizontal spread of each distribution trendline indicates a lot of variation across indvididuals within the same skill group.

Figure 9 shows a scatter plot of the response time versus Fitts' Index of Difficulty (ID). The x-axis is the ID score and the y-axis is the response time. Each point is the time it took

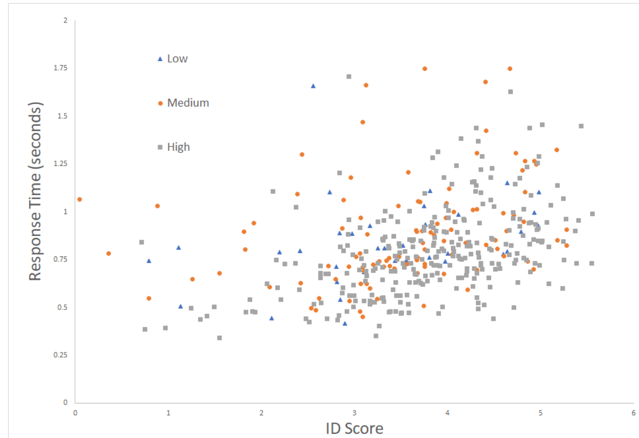


Figure 9: Response time versus ID score.

to select a target with the ID computed based on the target distance from the center and the target width. The point shapes and colors differentiate the self-rated skill groups for each user: low, medium and high. From the figure, there is a visual upward trend, left to right, as ID scores increase in response time, confirming Fitts' Law [4]. There is considerable variation, however, in that response times vary even the same ID score. This is to be expected given the natural variation in reaction times, demonstrated above. Visually, it is difficult to discern differences in response time for the different skills groups.

Since Fitts' law states there is a linear relationship between the response time and ID, we do a linear regression for each of the skill groups. Table 6 provides the results. The first column is the skill group, the second and third are the the line fit slope and y-intercept, respectively, and the last column is the coefficient of determination (R^2). From the table, Fitts' law explains about ZZZ% of the variation in response time overall, about 10% for low- and medium self-rated skills up to 20% for high self-rated players.

Table 6: Linear regression for dexterity task.

Skill	Slope	Y Intercept	R^2
Low	0.07	0.62	0.10
Medium	0.08	0.62	0.08
High	0.11	0.38	0.20
All	0.08	0.49	0.12

Figure 10 depicts response time versus skill for the dexterity task. The x-axis is the self-rated skill and the y-axis is the response time. Each data point is the average response time for all users in that category shown with a 90% confidence

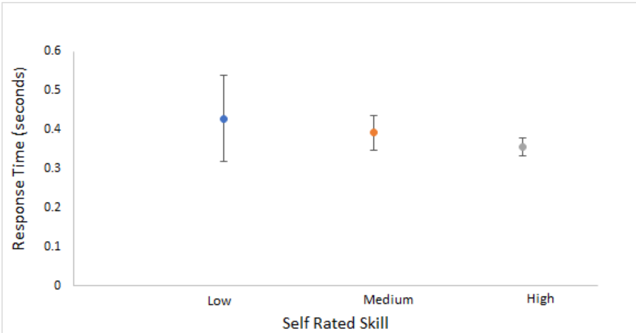


Figure 10: Average response time for dexterity task.

interval. From the figure, there is a visual downward trend in mean response time as skill group increases. However, there is some overlap in the confidence intervals.

There was a significant effect of self-rated gamer skill on response time for the dexterity task at the p<.1 level for the three conditions (F(2, 83) = 3.39, p = 0.038. T-test results ($\alpha = 0.1$) are shown in Table 7, with columns and comparisons as for. Table 5. From the Table, differences in adjacent skill groups are not significant, but the difference in skill group medium to high is significant even using a Bonferroni correction.

Table 7: T-test for dexterity task.

Comparison	t-Statistic	p value	d
Low - Med.	t(26) = -0.62	0.268	0.231
Med. - High	t(77) = 2.57	0.006	0.582
Low - High	t(63) = 0.92	0.180	0.407

5 CONCLUSION

The growing popularity of computer games means there are more people that may have response times that improve over those that do not play games for game-related tasks. In particular, real-time games often require quick reflexes and dexterity as well as require fast decision-making.

This paper presents results from two users studies evaluating the reaction time for self-rated gamers and performance along two dimensions: decision complexity, in the form of 1, 2 and 3 choices, and dexterity, in the form of targets of varying sizes and distance as in Fitt's Law. Analysis of results from over 150 participants shows small effects of self-rated gamer skill on reaction time, but moderate effects on task decision complexity for 1, 2 and 3 choices and dexterity in selecting targets of varying distance and size.

There are several areas of future work that might be promising. The axis of decision complexity can involve many more choices, as is the case for many games, and can involve much more information, in particular visual information as to what is happening in the game world, that may impact response time. Gamer skill can be assessed through multi-questionnaires, differentiating skills with different types of games (e.g., fast-paced versus strategy) and those results correlated with response time performance. Users studies could include a wider range of demographics (e.g., age) to more broadly apply to the gamer population at large.

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