XXXX X IML Collaboration Project Report:
Measuring XXXX Player's Physical and Cognitive performance

Exploring synergetic opportunities in professional gamers
and Human Computer Interaction researshers

March 2020

Introduction

Esports is sports; this is the foundational idea that initiated our current research project. The economic values and market size of Esports have been skyrocketing each year. With such an influx of attention, Esports eco-systems, such as league operations and player management, are resembling more like other traditional sports in many aspects. However, unlike other conventional sports, Esports still lack scientific approaches, especially in player training and drafting. Researchers from diverse scientific fields, from physiology, biomechanics, kinesiology to sports medicine, have been supporting the advancement of the performances of traditional sports athletes. We believe that similar cooperation is evident in Esports as well. Since it involves dynamic interaction between players and computers, different scientific approaches are necessary, such as Human-Computer Interaction. As Human-Computer Interaction researchers ourselves, we believe that we can create synergetic results via various cooperation like the current visiting opportunity.

According to many FPS game players, to defeat opponents in the game requires two essential abilities: mechanics and strategy. Of those, we have focused on the individual player's personal *physical* and *cognitive ability*, which define the mechanics. To compare the performance individually, we tried to quantify and measure the abilities based on the mathematical models. So far, we have completed numerous research on measuring cognitive abilities; the papers '*Temporal Pointing*[1]', '*Moving Target Selection*[2]', and '*ICP Model*[3]' have been verified and submitted to the ACM CHI conference, a top-tier conference on the Human-Computer Interaction field.

Further, we are currently developing a study to measure their physical abilities. In doing so, we had this fantastic opportunity with the XXXX team to experiment on top professional FPS game players carefully. During this visit, we conducted an experiment with three tests on the XXXX players, which have been verified to measure cognitive abilities. In this report, we will explain the experiment and interpretation of the results of each test in a detailed manner. Also, at the end of this report, we show the direction of our research and possible future plans.

[1]Lee, B., & Oulasvirta, A. (2016, May). Modelling Error Rates in Temporal Pointing. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (pp. 1857-1868). ACM.

[2]Lee, B., Kim, S., Oulasvirta, A., Lee, J. I., & Park, E. (2018, April). Moving Target Selection: A Cue Integration Model. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (p. 230). ACM.

[3]Park, E. & Lee, B. (2020, April). An Intermittent Click Planning Model. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. ACM. (Accepted)

Experiments

We conducted three experiments to measure quantitatively cognitive ability (performance) of each XXXX players: 1) Moving Target Selection test, 2) Pointing test, and 3) Reaction test. A total of 10 gamers, including the coach, participated in the experiments from 0/00 (000) $\sim$ 0/00 (000). The result data of each test are analyzed based on the mathematical models related to the human's cognitive characteristics. Before we report the results of our experiment, we briefly introduce the three tests used in the experiment.

Moving Target Selection (MTS) Test

Figure 1: Moving Target Selection test

Internal Clock: Internal clocks are hypothetical mechanisms in which a neural pacemaker generates pulses, with the number of pulses relating to a physical time interval recorded by some sort of counter.

Task description

The MTS test is an experiment to examine how accurately participants can predict precise timing. In a test, a small target (1 pixel of the strap) moves from left to right at a specific speed on a LED strap, and the selection region (is stationary and the size of the region varies depending on the experiment condition) is given on the strap. Then, participants have to click the mouse button when the target comes in the selection region. At this time, the participants rely on their own two cognitive information to predict the timing accurately: 1) their own rhythm using their internal clock, and 2) visual information given from the target and the selection region. This experiment tested the players' performance of predicting the exact timing using the two cognitive information.

Experimental procedure

XXXX players sat on a regular office chair and looked at the LED strap placed on the wall 2.8 meters away. The LED strap was installed horizontally at the eye level of the players, and we aligned the center of the selection region in front of players. After the brief introduction, each players was given a practice session until accustomed. Players were then asked to select as many targets as possible. There were eight experimental conditions (speed of the target, size of the selection region, the position of the target appears), and the players were asked to carry out 60 trials per each condition. We accumulated data of 480 trials from each player. The task took less than 20 minutes per players.

Analysis model

The result data of the MTS test was analyzed by the MTS model[4]. (Using the equation from the model, we can calculate quantitatively the extent of difficulty of each task with various conditions, respectively. As a result, the model allows us to predict how much error rates the participant will generate at each difficulty level.) From the

[4]Lee, B., Kim, S., Oulasvirta, A., Lee, J. I., & Park, E. (2018, April). Moving target selection: A cue integration model. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (pp. 1-12).

model, we can draw four parameters related to cognitive characteristics by regression analysis. Each parameter means 1) how accurately the player predicts the timing, 2) how consistently the player predicts the timing(related to a standard deviation of the click timing distribution), 3) how efficiently the player processes the information in the same amount of time to predict the timing, and 4) minimum error that the player can occur in the given task. We will explain more details in the result section below.

Pointing Test

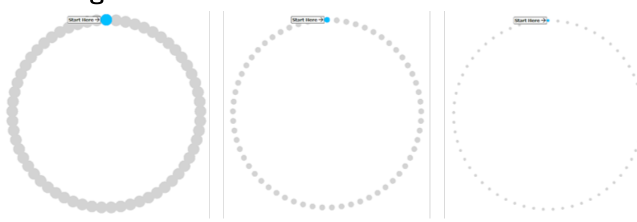


Figure 2: Pointing test

Task description
The pointing test was conducted to measure how fast and accurately the players click the given targets. The targets are positioned to form a circle, as shown in Figure 2. The test starts when a participant clicks the blue target. The next target is also marked in blue on the opposite side of the circle(the distance participants have to move the mouse to click the next target is equal to the diameter of the circle).

Experimental procedure
Players were asked to sit at a regular office desk in their most comfortable posture facing the computer screen where the task was shown and placing the primary hand on the mouse. The experimenter briefly introduced the task, and each player performed a practice session. Then, the players were asked to click the circles as quickly and accurately as possible in the clockwise order. There were six experimental conditions(size of the blue target circle, the distance between the targets), and the players were asked to carry out 60 trials per each condition. We accumulated data of 360 trials of pointing tasks from each player. The task took around 10 minutes per player.

Analysis model
This test is devised to verify the Fitts' law[5] by Wobbrock[6]. The main purpose of this model is to predict the movement time when the participants perform the pointing task with various conditions of difficulties. To measure aim performance using this model, we focused on comparing the pointing speed of each player. Also, we compared the performance between a professional gamer (pro-gamer) group and a normal gamer.

Reaction Test

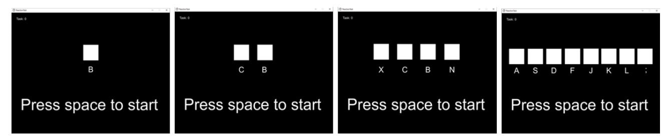


Figure 3: Reaction test

Task description
The reaction test is an experiment to examine players' reaction times of pressing key buttons on keyboards. In the test, an 'X' mark appears on the different targets, and the players had to press the appropriate buttons as quickly

[5] Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. Journal of experimental psychology, 47(6), 381.

[6] Wobbrock, J. O., Cutrell, E., Harada, S., & MacKenzie, I. S. (2008, April). An error model for pointing based on Fitts' law. In Proceedings of the SIGCHI conference on human factors in computing systems (pp. 1613-1622).

and accurately as possible. The test consists of a simple reaction task and multiple-choices reaction task to measure both 1) physical reaction capacity and 2) cognitive information processing capacity. Recorded data is the reaction time of each button pressing.

Experimental procedure
First, players were asked to sit on a desk in their most comfortable posture facing the computer screen where the test was displayed. Then, we asked them to place either both or one hand on the keyboard, which they want to use to perform the test. We briefly introduced the test, and each player performed a practice session. Then, before the actual session started, we asked players to press the right keyboard button as quickly and accurately as possible. There were a total of four different conditions; 1, 2, 4, and 8 target keys. Each condition had 30 trials, and a total of 120 trials were performed by each player. The test took around ten minutes per player.

Model Fitting: Fitting data into a model provides a measure of how well a model generalizes to real-world data. By fitting the obtained data from the experiment, we can derive specific parameters from that particular data.

Analysis model
To analyze the performance of players, we applied Hick-Hyman Law[7]. The law describes the time it takes for a user to make a decision given available targets. It demonstrates that increasing the number of choices would increase the decision time logarithmically. With this law, we could calculate two free parameters for each player fitted from recorded experimental data of their reaction times; first is intuitive reaction time, and second is a cognitive information processing capacity. In more Overwatch related terms, first, intuitive reaction time can be thought of as to how quickly click a single skill versus cognitive information processing capacity as to how promptly click a combination of skills. Combining these two parameters, we compared the capacity of each player on how quickly presses the correct buttons.

Moreover, we devised four different choice conditions into two groups. The first group, 1 and 2 choice conditions, is meant to measure the intuitive reaction time and second group, 4 and 8 choices conditions, are intended to measure the cognitive information processing capacity.

Result

Last fall, we had conducted the pilot experiment that was the same as the experiment we had for this time. During the pilot experiment, we recruited participants from three groups varying in their ability to play FPS game: 1) B pro-gamer group, 2) Elite gamer group (grandmaster or master in Overwatch), and 3) Normal gamer group (gold or silver in Overwatch). In this section, we will present two different results. First, we compared the differences between the four groups (above three groups from the pilot experiment and XXXX team) and then, we analyzed the individual differences among the XXXX players.

Moving Target Selection(MTS) Test
Using the MTS model, we can calculate the quantitative extent of difficulty of each task with various conditions, respectively. We represent this as 'Index of Difficulty' in Figure 4. An bigger index on the X-axis indicates the task condition was more difficult than a smaller index. As a result, the fitted model(equation 1) allows us to predict how much error rates the participant would generate at each index of difficulty.

$$E = 1 - \frac{1}{2}[erf(\frac{(1-c_\mu)}{c_\sigma\sqrt{2}} \cdot \frac{W_t}{D_t}) + erf(\frac{c_\mu}{c_\sigma\sqrt{2}} \cdot \frac{W_t}{D_t})] \quad (1)$$

[7] Seow, S. C. (2005). Information theoretic models of HCI: a comparison of the Hick-Hyman law and Fitts' law. Human-computer interaction, 20(3), 315-352.

$$D_t = P/\sqrt{1 + (P/(1/(e^{\nu t_c} - 1) + \delta))^2} \qquad (2)$$

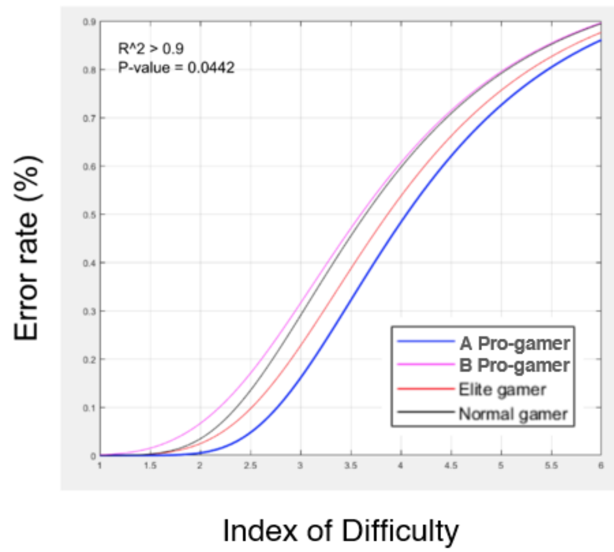


Figure 4: Result of data fitting based on Moving Target Selection model

R^2 **(Coefficient of determination) Value:** it is the proportion of the variance in the dependent variable that is predictable from the independent variables. It provides a measure of how well observed outcomes are replicated by the model. The value normally ranges from 0 to 1 and as it is closer to 1, the model performs better.

As you can see in Figure 4, the players of XXXX (A pro-gamer in the figure) are predicted to generate the lowest error rates across all difficulty levels. This means that regardless of the difficulty, XXXX players outperform with lower error rates. For example, if we zoom into the 3.5 index of difficulty in Figure 5, it is expected to produce the lowest error rate in the following order: A pro-gamer (XXXX players), Elite gamer, Normal gamer, and B (Battleground) pro-gamer. It is peculiar that B pro-gamers are expected to generate the highest error rate. We presumed that it is related to the control of the experiment environment; because the experiment with the B pro-gamer group was performed first, we were less rebust about controlling the experiment environment. We learned about this previously, and for this experiment with XXXX players, we tried our best to keep the environment as controlled as possible.

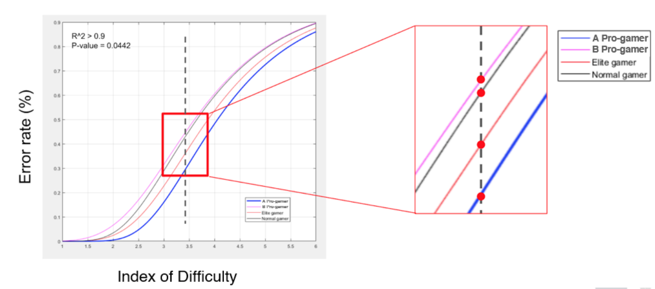


Figure 5: Predicted error rate of each group at the same index of difficulty (3.5)

We calculated the R^2 value, which indicates the reliability of fitted results; as the R^2 value is closer to 1, it is more reliable. In our analysis, we have '$R^2 > 0.9$,' which means the data of each group was well fitted to the Moving Target Selection model.

Parameters from the model
We used the same analysis code to analyze the data of XXXX players and the data of the other groups. '$\mathbf{c}_\mu$', '$\mathbf{c}_\sigma$', '$\boldsymbol{\nu}$', '$\boldsymbol{\delta}$' in Table 1 are the parameters generated from the result of fitting the model. We will explain each one in detail below.

		$c\mu$	$c\sigma$	ν	δ
A Pro-gamer	mean	0.490	0.045	50.985	0.440
	median	0.500	0.042	41.402	0.437
B Pro-gamer	mean	0.254	0.049	62.537	0.480
	median	0.278	0.054	82.627	0.500
Elite gamer	mean	0.307	0.062	37.997	0.395
	median	0.317	0.057	36.543	0.432
Normal gamer	mean	0.275	0.066	51.269	0.492
	median	0.292	0.058	44.897	0.451

Table 1: Four parameters of each group drawn from the MTS model

		$c\mu$	$c\sigma$	ν	δ
XXXX pro-gamer	Player 1	0.500	0.046	18.987	0.437
	Player 2	0.500	0.054	99.877	0.282
	Player 3	0.500	0.036	41.402	0.493
	Player 4	0.500	0.041	53.221	0.507
	Player 5	0.463	0.065	99.985	0.367
	Player 6	0.500	0.045	20.565	0.666
	Player 7	0.500	0.037	12.973	0.497
	Player 8	0.500	0.036	18.205	0.419
	Player 9	0.430	0.040	10.414	0.292
	Player 10	0.500	0.042	85.670	0.469
	Player 11	0.500	0.058	99.531	0.416

Table 2: Four parameters of each XXXX players drawn from the MTS model

One-way ANOVA (analysis of variance) Testing: it is a technique that can be used to compare means of two or more samples. Basically, it is testing groups to see if there is a significant difference between them

First of all, the mean and median $\mathbf{c}_\mu$ value of XXXX players is about 0.5 (in Table 1). It is higher than other groups' $\mathbf{c}_\mu$ value. As you see in Figure 6, the fact that $\mathbf{c}_\mu$ is 0.5 means the user aims at the center of the target (Selection region). That is the optimal aim point($\mathbf{c}_\mu$=0.5), according to the model. However, users typically aim for the beginning of the target where $\mathbf{c}_\mu$ is less than 0.5 (including other groups such as B pro-gamer, Elite gamer, and Normal gamer). We guess the reason that the users tended to click ahead before the flying target reaches to the center because they thought the strategy is safer for success in the task. The $\mathbf{c}_\mu$ value may vary depending on the aiming strategy. In many of the experiments we have done so far, we have got the most values less than 0.5 from the different user groups. However, it is impressive to see many results with 0.5 as $\mathbf{c}_\mu$ from the XXXX players.

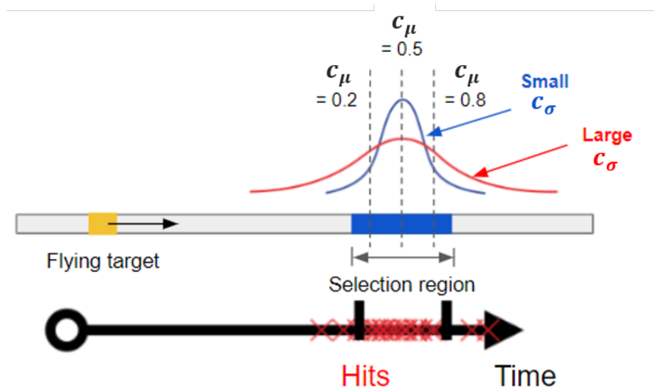


Figure 6: Meaning of $\mathbf{c}_\mu$ and $\mathbf{c}_\sigma$

Next, $\mathbf{c}_\sigma$ represents how narrow the distribution of hit points is, and the narrow distribution is proof of better performance. This means that the smaller the value of $\mathbf{c}_\sigma$, the narrower the distribution, as shown in Figure 6. This $\mathbf{c}_\sigma$ represents as an internal clock rhythm of each user, and the narrower distribution means a more consistent internal clock rhythm. Following our expectation, $\mathbf{c}_\sigma$ values of XXXX players groups were much smaller than those of other groups. To verify the validity of the difference of mean $\mathbf{c}_\sigma$ value of each group, we conducted a one-way ANOVA test, which is a technique that can be used to compare means of two or more samples. As a result of the test, it provides a p-value that tells us how valid the differences of means between groups is. Generally, if the p-value is smaller than 0.05, we can say that there is a significant difference in the mean values among the groups. We have got 0.0442 (< 0.05), which shows that the difference in means of $\mathbf{c}_\sigma$ was meaningful. We also compared the results using the box plot below to reveal the better performance of XXXX team pro-gamers visually.

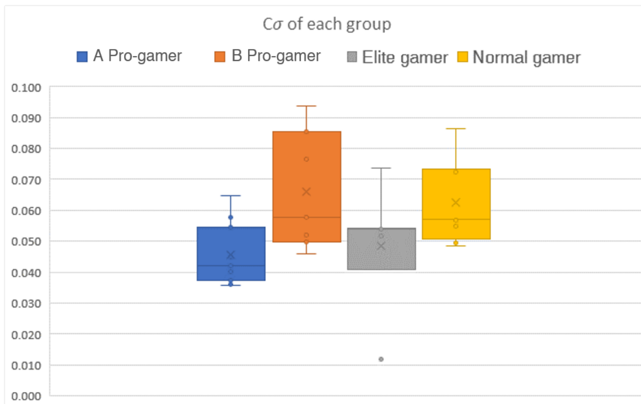


Figure 7: $\mathbf{c}_\sigma$ of each group

In this section, we will introduce the remaining cognitive information that was necessary to complete this task successfully. We mentioned that the participants rely on their two cognitive information to successfully perform this task. The first was their own rhythm using their internal clock, and the second was the visual information given from the flying target and the selection region. Here, $\boldsymbol{\nu}$ represents the rate of how much the user relies on visual information. Further, a higher value means that the user depended more on visual information. According to the MTS model, the $\boldsymbol{\nu}$ value is very user-dependent and varies highly depending on the strategy the user preferred. Due to such characteristics, there was no significant difference in means of $\boldsymbol{\nu}$ between the four groups.

The $\boldsymbol{\delta}$ means the minimum error rate that can occur even when the user performs a task that the target flies very slowly (in the most straightforward task). Similar to $\boldsymbol{\nu}$, there was no significant difference between $\boldsymbol{\delta}$ values of the four groups.

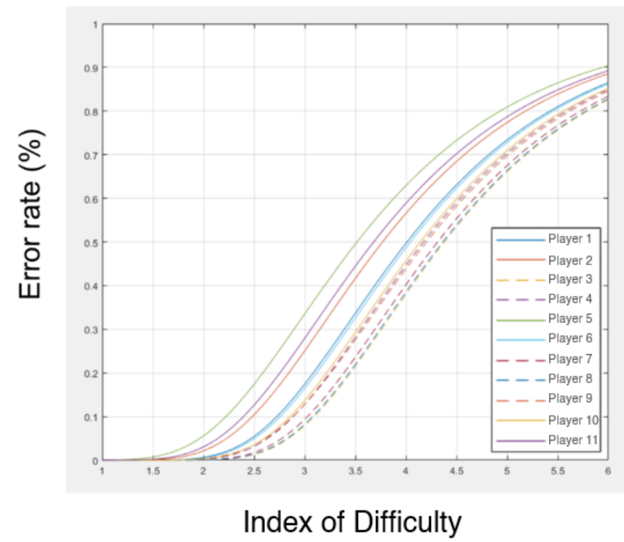


Figure 8: Result of data fitting for each XXXX player

As we show the fitting results for each group above(in Figure 4), we proceeded with the model fitting of individual XXXX players(in Figure 8,9). The factor most relevant to the error rate is $\mathbf{c}_\sigma$, and the MTS-1 column of the leaderboard is sorted by the player with the lowest predicted error rate. (Player 3 is in the first place)

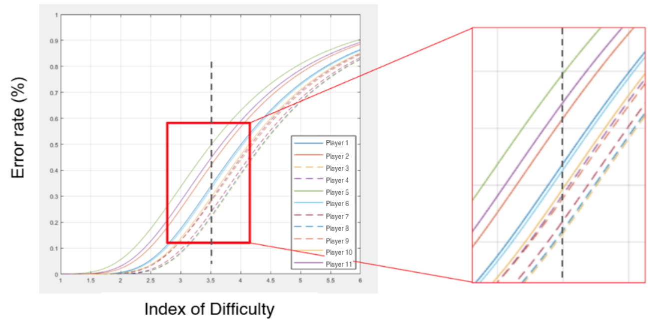
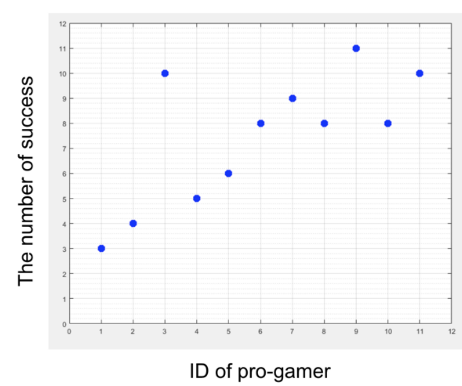


Figure 9: Predicted error rate of each XXXX player at the same index of difficulty (3.5)

Additionally, we conducted one more experiment with another condition with a very small selection region(Additional condition in Figure 10 can be regarded as a very challenging condition). This condition has not been tried out by other groups. So, we only analyzed and compared the individual results within the XXXX player group. We analyzed the results in two methods: 1) Compared the number of successes (target clicked in the selection region), and 2) Compared the variance of each player's click point distribution (Like $\mathbf{c}_\sigma$ in Figure 6).

Figure 10: Original condition and additional condition of the MTS test

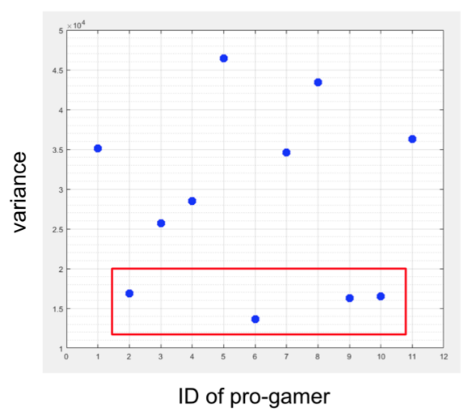
First, we counted the number of successes each player achieved. X-axis and Y-axis represent the ID of a player and the number of successes(score), respectively. The best score was 11 performed by Player 9. Player 3 and Player 11 got 2nd place following Player 9. However, the selection region was very small(it was just 1 pixel of the LED strap), and if a player had clicked the pixel very right next to the target, the trial was counted as a fail. So, we doubted the number of successes could indicate the player's performance correctly. We concluded, rather, the variance would be an appropriate index correlated to the performance.



ID	Name
1	Player 1
2	Player 2
3	Player 3
4	Player 4
5	Player 5
6	Player 6
7	Player 7
8	Player 8
9	Player 9
10	Player 10
11	Player 11

Figure 11: Result of the additional condition of MTS test (number of successes)

Comparing the variance, Player 6 got the smallest variance that means the points he clicked are distributed closest to the selection region compared to other player's results. Player 2, Player 9, and Player 10 in the red box in Figure 12 also attained small variance following Player 6.



ID	Name
1	Player 1
2	Player 2
3	Player 3
4	Player 4
5	Player 5
6	Player 6
7	Player 7
8	Player 8
9	Player 9
10	Player 10
11	Player 11

Figure 12: Result of the additional condition of MTS test (Variance of the click point distribution)

Pointing Test

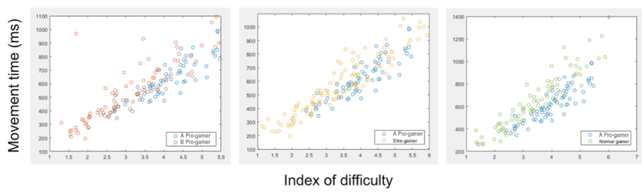


Figure 13: Pair-wise comparison of the movement time by four group

According to Fitts' law, if a width (W) of the circular target (diameter of the target) and a distance (D) between the two targets are given as variables in a pointing test, we can calculate an index of difficulty (ID) for each task condition.

$$ID = log_2(\frac{2D}{W}) \qquad (3)$$

$$MT = a + b \cdot ID = a + b \cdot log_2(\frac{2D}{W}) \qquad (4)$$

In Figure 13, the blue circles refer to the movement time of the A pro-gamer group spent for each pointing task during the test with the various conditions. The red circles, yellow circles, green circles indicate the movement time of the B pro-gamer group, Elite gamer group, and Normal gamer group, respectively. In all the three figures of the Figure 13, we can see roughly the blue circles are positioned below the other color circles (Failed tasks are not contained in the figures. Only succeeded tasks are plotted). XXXX players tended to complete each task in a shorter time than the other groups across the whole range of the index of difficulty.

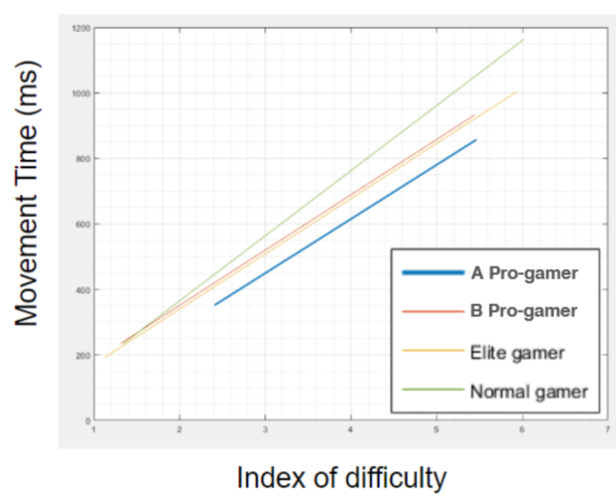


Figure 14: Comparison of the movement time by four groups

Through the linear fitting using the data from the pointing test, we plotted the fitted regression lines representing the movement time (Equation 4) for the four groups. As you see in Figure 14, the blue line (XXXX players) is far below the others.

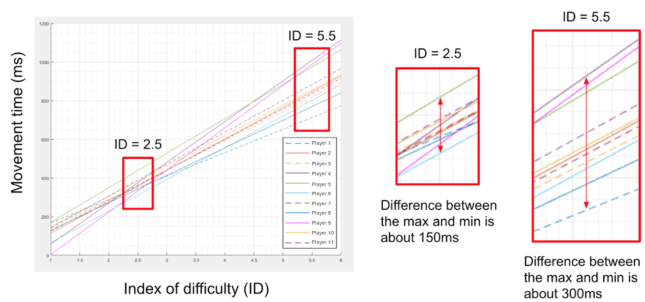


Figure 15: XXXX players' movement time

We also compared the fitted line individually for each player. The index of difficulty (ID) of the easiest condition given in this test was 2.5, and the hardest condition's index of difficulty was 5.5. Therefore, values outside the range of 2.5 to 5.5 are predicted movement time by the linear regression. In the case of the ID is 2.5, a difference between the fastest movement time and the slowest one was 150ms. Player 6 showed the fastest pointing speed with the shortest movement time for the easy conditions. However, in the difficult conditions with high ID (5.5), Player 1 and Player 8 were faster than Player 6. The maximum difference of the movement time in the hard condition was 300ms.

ID	Name	a	b
1	Player 1	46.89	121.04
2	Player 2	-48.26	162.76
3	Player 3	-13.08	151.23
4	Player 4	-152.62	211.18
5	Player 5	-7.57	178.59
6	Player 6	-98.18	163.75
7	Player 7	-33.51	158.18
8	Player 8	-12.64	142.19
9	Player 9	-213.74	218.45
10	Player 10	-8.54	157.19
11	Player 11	-22.55	164.85

Table 3: Individual a, b parameters of *Equation 4*

Reaction Test

As mentioned in the previous section, we used Hick-Hyman Law to analyze the intuitive reaction time and cognitive information processing capacity of the players. If you see the below Figure 16, you can see that each parameter represents the capacities that we would like to discover from this experiment. Here, '**RT**' represents the reaction time calculated by the equation and '**N**' is the number of available choices. From the experiment, we can collect a user's reaction time data (RT) for different choice availabilities (N). Then, we can fit these data into the Hick-Hyman Law equation and get the fitted parameters of '**a**' and '**b**'.

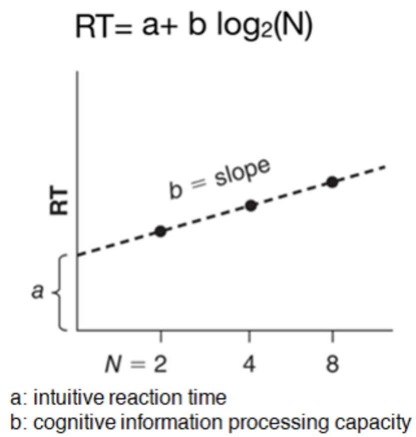


Figure 16: Hick-Hyman Law equation and graphical representation of the law

Using the collected data from the XXXX players, we fit the data into the Hick-Hyman Law equation and got fitted parameters of *a* and *b*, as a group as well as an individual.

Similar to other tests, we first compared the results of the XXXX players group to other gamer groups from our previous experiment. Figure 16 displays the four groups' reaction time predictions of the Hick-Hyman Law equation. The blue line (A labeled) at the lowest position is the result of XXXX players. This illustrates that among four groups, XXXX players demonstrated the quickest reaction time across different levels of difficulty. One caveat is that we used different keyboards for each of the experiments, and because each keyboard has different activation points, it may have affected the reaction time results.

Nonetheless, overall, XXXX players were *50 milliseconds* quicker in reaction time than the next faster group, Elite games in yellow line (see Figure 17. A pro-gamer group is XXXX players, B pro-gamer group is Battleground pro-gamers). To see whether these differences among groups are significant, we conducted a one-way ANOVA tests for each of the actual testing conditions, 1 choice, 2 choices, and 4 choices. Rectangular boxes represent these actual testing levels. Red boxes, 1 choice and 2 choices, are where the differences were statistically significant (** $p<0.05$). However, 4 choices in the yellow box was not statistically significant ($p=0.34$). To summarize, our first analysis revealed that XXXX players comprehensively outperform other groups throughout all levels of difficulty. Moreover, because their performance in the first two conditions (1 and 2 choices) is statistically significant, we can assert that XXXX players have faster reaction times than any other group.

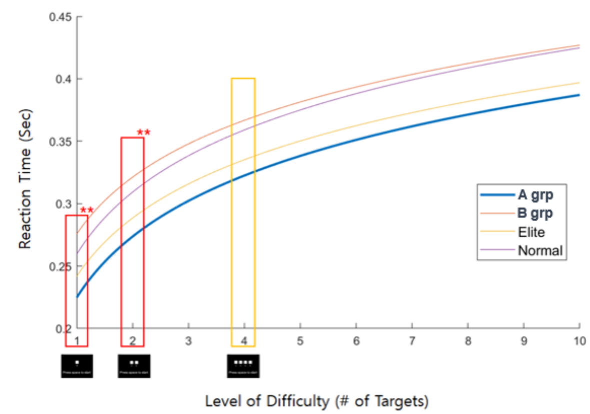


Figure 17: Comparison of data fitting by four groups

Next, we analyzed individual differences among XXXX players and plotted the same fitting graph in Figure 18. For the individual differences, all four different conditions

(1, 2, 4, and 8 choices) were statistically significant.

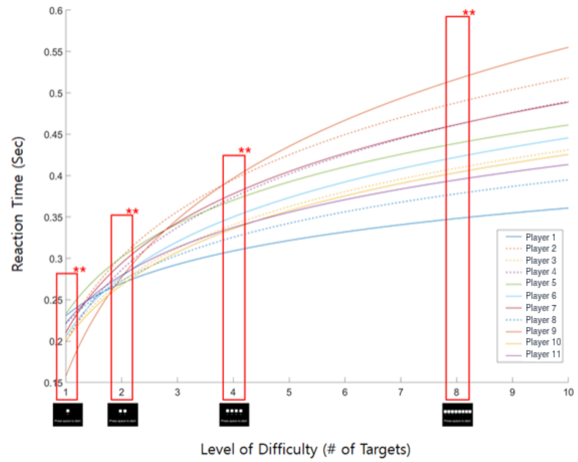


Figure 18: Comparison of data fitting by individual XXXX players

One interesting finding from the analysis of individual differences is shown in the next figure (Figure 19). In the figure, Player 9 (#1 in orange) and Player 1 (#2 in blue) depict two opposite trends. If you see the green dashed-box 1, Player 9 is much faster than Player 1 in reaction time. However, as the available choices increase, the order of their reaction times changes; after the crossing point in red dashed-circle, Player 1 stays faster than Player 9 in reaction time. This is a glaring illustration of two free parameters, each explaining 1) intuitive reaction time and 2) cognitive information processing capacity. Player 9 demonstrated fast intuitive reaction time while weak cognitive information processing capacity. On the other hand, Player 1 demonstrated slow intuitive reaction time while strong cognitive information processing capacity. From the analysis, we could conspicuously capture different trends among players.

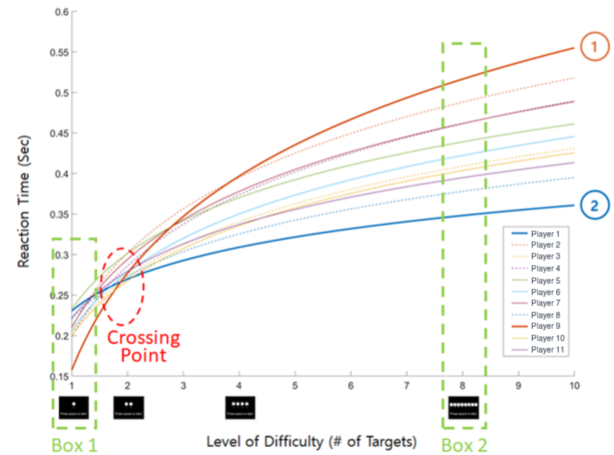


Figure 19: Predicted individual performance patterns of the fitted data

Finally, below Figure 20 shows the lists of XXXX players in each of the four conditions. For the single choice condition, Player 9 showed the quickest reaction time; the difference between the quickest and slowest reaction time was less than 7ms. For the 2-choices condition, Player 9 Still showed the quickest reaction time; the difference between the quickest and slowest reaction time was less than 10ms. For the 4-choices condition, Player 1 showed the quickest reaction time; again, the difference between the quickest and slowest reaction time was less than 10ms. Lastly, for the 8-choices condition, Player 1 showed the quickest reaction time; here, the difference between the quickest and slowest reaction time was around 20ms.

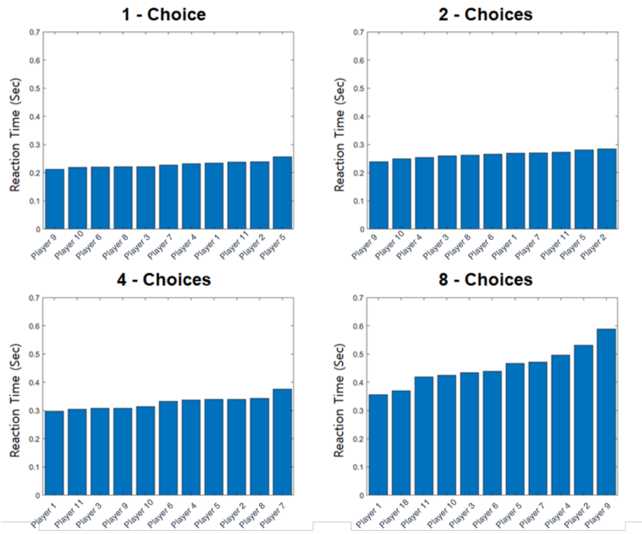


Figure 20: Lists of reaction time for individual XXXX players by four conditions

Discussion

In table 4, we listed up the XXXX players in the order of their performance. You can think of the leftmost numbers as ranks. Of course, we cannot conclude that the results of this experiment are directly related to their game skills. Still, it was interesting that in the leaderboards, every first-ranked player in each experiment belongs to the dealer position. Because of this result, we wondered whether the cognitive performance trend of players differs depending on the meta position of the players.

In general, the experimental results showed that the performance of XXXX players was superior to that of other groups. After the data analysis, we have been left with several questions that demand further investigations. The first one is $\mathbf{c}_\mu$ values of 0.5 for all of the XXXX players in the Moving Target Selection test. Theoretically, although an optimal $\mathbf{c}_\mu$ value is 0.5, we could not have seen that a $\mathbf{c}_\mu$ of 0.5 is extracted from a specific group during our other pilot studies so far. We wonder what factors made this difference, given that all the experimental and analytical conditions were the same.

The followings are possible practical applications of our three tests into actual in-game situations. First, the critical component from the MTS test is the internal clock; within the game, this can be situations where specific tempo or rhythms are required. In Overwatch, it can be the charging rhythm of Widowmaker's zoom, bow tension of Hanzo's shoot, or left-click shooting of Macree. Second, the Pointing test can tell us the precise mouse movements; it can be thought of as any aim-click execution within the game. In Overwatch, most sniper-type characters (Ashe, Ana, or Widowmaker) typically require such precise aim-click executions to kill enemies. Lastly, the Reaction test can tell us a straightforward reaction in pressing a single keyboard button or a combination of buttons within the game. In Overwatch, it can be thought of as pressing 'Shift,' 'Ctrl,' 'E,' and other skill buttons consecutively, correctly, and in a proper situation.

Limitation

Furthermore, we found that the players were very keen about using different gears; for this experiment, we asked players to use their own mouses and mouse pads, but not the keyboards. However, if it was to be a precise experiment, all players had to use the same gears. We do know that the players are very delicate about using their own gears to play the actual game. However, we cannot claim anything about the role of gears on the physical

	MTS-1	MTS-2 (Score)	MTS-2 (variation)	Pointing (easy)	Pointing (hard)	Reaction-1	Reaction-2	Reaction-4	Reaction-8
1	Player 3	Player 9	Player 6	Player 6	Player 1	Player 9	Player 9	Player 1	Player 1
2	Player 8	Player 3(2)	Player 9	Player 9	Player 8	Player 10	Player 10	Player 3	Player 8
3	Player 7	Player 7	Player 10	Player 8	Player 6	Player 6	Player 4	Player 9	Player 10
4	Player 9	Player 6(4)	Player 2	Player 1	Player 3	Player 8	Player 3	Player 10	Player 3
5	Player 4	Player 8(4)	Player 3	Player 2	Player 7	Player 3	Player 8	Player 6	Player 6
6	Player 10	Player 10(4)	Player 4	Player 7	Player 2	Player 7	Player 6	Player 4	Player 5
7	Player 6	Player 5	Player 7	Player3	Player 10	Player 4	Player 1	Player 5	Player 7
8	Player 1	Player 4	Player 1	Player 4	Player 5	Player 1	Player 7	Player 2	Player 4
9	Player 2	Player 2	Player 8	Player 10	Player 9	Player 2	Player 5	Player 8	Player 2
10	Player 5	Player 1	Player 5	Player 5	Player 4	Player 5	Player2	Player 7	Player 9

	DPS
	SUP
	TNK

Table 4: Leaderboard of overall experiments

level performances; this is another area to be further developed in the future.

Future Plan

Contemporary sports have evolved to recognize an athlete's physical capacity in many dimensions. One most notable successes are the draft camps. Under the name of 'Combine,' professional sports leagues, especially basketball and football, have annually organized and run the draft camps to both discover 'hidden gem' athletes for the clubs as well as to provide opportunities for prospective athletes. Typical programs of the combines include low-level physical measurements such as a *40-Yard Dash* or *Vertical Jump* to actual performance measurements such as skill drills or short scrimmages. Such physical ability data of players are openly distributed on their official websites for both teams and other players[8].

Yet, Esports is still an area where coaches and scouts' gut feelings dominate in scouting and selection of players. Most decisions are made by watching the prospective player's performance videos. Different leagues have just recently launched their beta services on providing in-game statistics, for instance, Stats Lab for Overwatch league[9]. Yet, we believe that there are very few teams that actually appropriate such data into their training, and XXXX has been taking very innovative yet experimental steps in this manner. As E-sports itself grows, each team would demand a much more robust database, especially in low-level physical capacities. And, there, we believe that our research area of Human-Computer Interaction can take part in and generate valuable benefits for the team

[8] NBA Draft Combine Statistics summarized page https://stats.nba.com/draft/combine/

[9] Overwatch Stats Lab Beta service page https://overwatchleague.com/en-us/statslab

and players using scientifically proven models and data analysis.

Figure 21: Draft combines of NFL and NBA

In addition to three experiments conducted on this trip, there are various other physical ability measurement tools in our lab that we could not bring. To list a few, we have a multi-sensors logging system that records eye movements, motion tracking, pulse, and muscle activities simultaneously. Further, we have several programs that can measure moving target click performance as well as time-pressure related performance. Using these resources allows us to measure various other physical ability data and ultimately generate a more comprehensive statistical analysis, such as differences in physical capacity among three positions or correlation of age differences.

Acknowledgement

Going beyond mere classification and evaluation of individual skills, implementing physical ability measurements is a step forward for Esports as being part of traditional sports. We strongly believe that utilizing such data and convening of various events will put momentum in attracting more exceptional aspirants and passionate fans.

We thank XXXX for taking the first big step in this direction with us, HCI researchers. Because of its dynamic interactions between players and computers, Esports is the most effective area for HCI research to be conducted. Similarly, Esports is a unique branch where a powerful medium of computer influences, and it would need a strong collaboration with HCI fields as well. We look forward to continuing our partnership so that we can conduct research that will help athletes to improve their skills as well as the advance of the Esports industry.

The report and analysis were developed by **Eunji Park**, Ph.D candidate and **Sangyoon Lee**, Master's candidate from Interactive Media Lab, KAIST, South Korea (March, 2020)