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UNDERSTANDING THE UTILIZATION OF INFORMATION STIMULI IN DESIGN DECISION MAKING USING EYE GAZE DATA

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ABSTRACT

Research on decision making in engineering design has focused primarily on how to make decisions using normative models given certain information. However, there exists a research gap on how diverse information stimuli are combined by designers in decision making. In this paper, we address the following question: *how do designers weigh different information stimuli to make decisions in engineering design contexts?* The answer to this question can provide insights on diverse cognitive models for decision making used by different individuals. We investigate the information gathering behavior of individuals using eye gaze data from a simulated engineering design task. The task involves optimizing an unknown function using an interface which provides two types of information stimuli, including a graph and a list area. These correspond to the graphical stimulus and numerical stimulus, respectively. The study was carried out using a set of student subjects. The results suggest that individuals weigh different forms of information stimuli differently. It is observed that graphical information stimulus assists the participants in optimizing the function with a higher accuracy. This study contributes to our understanding of how diverse information stimuli are utilized by design engineers to make decisions. The improved understanding of cognitive decision making models would also aid in improved design of decision support tools.

Keywords: Decision-making, eye tracking, information stimuli, information gathering

1 INTRODUCTION

Engineering design is increasingly being analyzed from the perspective of a decision making process [1, 2]. Understanding decision making in engineering systems design can help designers make better decisions. This boosts the research on decision making in engineering design focusing on various aspects, such as preference mining, decision structuring and evaluation.

From the designer's standpoint, information gathering and processing plays an important role in the process of decision making. Various tools have been developed to aid designers in information gathering, such as gathering information through various types of surveys [3], utilizing context specific tools such as the Delphi Method [4] and Bounded Information Gathering (BIG) [5]. Various comprehensive theories such as utility theory [6], game theory [7] and Discrete Choice Analysis [8] are also widely utilized in design decision making.

Although various information gathering tools exist for designers' aid, people perceive different kinds of information stimuli in different ways [9]. This in turn affects the way they make decisions. For example, some people prefer and perform best on decision tasks with verbal information, while others perform better with concrete, descriptive and pictorial information [10]. Thus to understand the way people weigh information stimuli would shed light on which cognitive processes are used by different people to make decisions in engineering design contexts. In this exploratory study, we addressed the following research question: *how do designers weigh different information stimuli to make decisions in engineering design contexts?*

To answer this question, we conducted an experiment in which participants were asked to complete a design task with various information sources on computer. We utilized a function minimization game proposed by Sha et al. [11] as a simulated

design task. This task involves optimizing an unknown function using a computer interface which provides two types of information stimuli, including a graph and a list area. These correspond to a graphical stimulus and numerical stimulus, respectively. We investigated which kind of information stimuli was more often used by the players and how such weightage on different information stimulus affected players' decisions.

Individuals' information acquisition process can be monitored by many process tracing methods, such as computer-based information board paradigms (e.g. Mouselab [12]) and think-aloud protocols [13]. However, these techniques sometimes influence decision behavior [14] and might hinder participants from relying on automatic processing by constraining quick comparisons and information search [15]. In contrast, eye-tracking technology allows for tracing information search without hindering automatic processes and participants fixation durations can be used to provide insights into cognitive processes [16]. In the context of our game where the eye-mind coordination is required to fulfill the task objectives, an eye-tracker was used to trace how players perceive different visual information from the user interface in the decision making process.

In the remainder of this paper, Section 2 provides background on design decision-making, cognitive styles and eye tracking methods. The experimental methods and results are presented in Sections 3 and 4, respectively. Section 5 provides conclusions and future work.

2 RELATED LITERATURE

In this section, we review the existing literature on decision making in design, the impact of individuals' cognitive styles on decision making and the application of eye-tracking in decision making. We show the research gap between decision making in design and understanding the cognitive styles of designers. Bridging this gap would help us understand how designers weigh different information stimuli to make decisions. We believe that eye-tracking is a promising tool to capture how individuals process visual information for decision making.

2.1 Decision Making in Design

Existing research on decision making in engineering systems design focuses on the type of the problem such as multi-attribute decision making [17], discrete choice analysis [18] etc. to elicit user preferences like preference based modeling [19], demand modeling [18], choice modeling [20]. However, these studies do not describe human information processing from basic principles of cognition and have broadly stated descriptions of theoretical assumptions. Behavioral experiments show that people tend to deviate from expected rational behavior [21] and people have bounded rationality [22]. These behavioral traits need to be incorporated within the decision making framework to understand how the decisions are made. Therefore, an alternative basis for mathematical modeling of decision making is needed.

Within the context of engineering design, designers need

various kinds of tools to analyze their decisions scientifically. Information gathering and information processing are important aspects while utilizing these tools. Tools such as BIG aid (Bounded Information Gathering) in this kind of information gathering and information processing using various unstructured and structured documents [5]. However these tools, models and frameworks do not incorporate how an individual designer's information perception and feedback could affect the decision making process. By using the principles of cognitive psychology through behavioral experiments such understanding of the decision making process could be achieved within the context of engineering design.

2.2 Cognitive Styles and Decision Making

Decision making consists of three interacting components, namely, the decision maker, the task, and the decision context or situation [23]. Researchers have noticed that decision makers' information processing styles or cognitive styles influence their decision making behavior [23]. According to Riding and Cheema [10], cognitive style is described as a person's typical or habitual mode of problem solving, thinking, perceiving and remembering. These styles are viewed as relatively stable dispositions which lead to differences in behavior in the decision-making process [24]. Henderson and Nutt found cognitive style to be an important factor in decision making and the assessment of risk [25].

Different researchers have used a variety of labels for the cognitive styles they have investigated, such as field dependence-independence [26], holist-serialist [27], diverging-converging [28] and verbalizer-visualizer [29]. Riding and Cheema suggested that these labels may be grouped into two principal cognitive styles (see Figure 1): (1) the holist-analytic style of whether an individual tends to process information in wholes or parts; and (2) the verbal-imagery style of whether an individual is inclined to represent information during thinking verbally or in images.

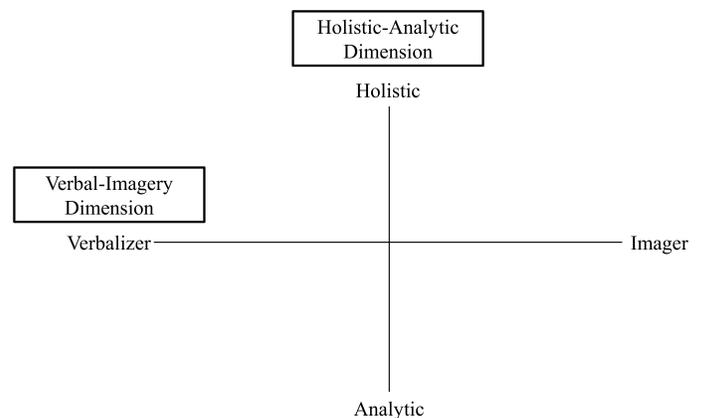


FIGURE 1. The two dimensions of cognitive style

Researchers have found that imagers learn best from pictorial presentation, while verbalizers learn best from text [30–32]. For example, Riding and Douglas investigated the effect of cognitive style and mode of presentation on learning performance [33]. In their study, secondary school students were presented the learning material about the working of car braking systems in text-plus-picture condition or text-plus-text condition. They found that in the text-plus-picture condition imagers were superior to verbalizers, while the text-plus-text condition verbalizers did better than imagers. It was also observed that imagers used more diagrams to illustrate their answers than verbalizers. Thus, players with different cognitive styles show behavioral differences in their decision making processes, including allocating different weightage on different kinds of visual information sources.

2.3 Research on Eye Tracking and Its Application in Decision Making

Eye-tracking research is based on Just and Carpenter’s eye-mind hypothesis [34] that people look at what they are thinking about. Accordingly, people fixate on a specific area of a problem diagram longer when they encounter difficulties or are confused. Although there are studies showing inconsistent results, it is widely agreed that during a complex information processing task such as reading, eye movements and attention are linked [35]. Recent advances in eye tracking, specifically the availability of cheap, faster, more accurate and more user-friendly eye trackers, enable researchers from areas besides psychology to apply this technology for the research on visual attention and thinking process [36–40].

The main metrics used in eye-tracking include: (1) fixations: eye movements that stabilize the retina over a stationary object of interest; (2) fixation time: a measure of the duration of the fixation; and (3) scan paths: connections between consecutive fixations [41]. The location and duration of fixations is directly related to the locus and difficulty of cognitive processing [42]. Thus, eye movements may provide insight into what visual information is being processed currently and how difficult this information is to process, which may serve as an additional measure for learning, problem solving and decision making processes [43].

In problem-solving area, researchers found that high performers and low performers show different eye gaze patterns (fixations, fixation duration, saccade length, etc.) while solving problems with visual elements [44]. For example, Madsen found that while solving physics problems, correct solvers spent more time attending to relevant areas, whereas incorrect solvers spent more time looking at novice-like areas [45]. Consistent results can also be found in Tsai et al.’s research on visual attention for solving multiple-choice science problem [46]. These results suggest that people’s problem-solving performances could be indicated by their eye gaze patterns to some extent.

Eye-tracking is increasingly used in decision making research. Kim et al. used an eye tracker to better understand

why participants with a variant of a tabular visualization called ‘SimulSort’ outperformed ones with a conventional table and typical one-column sorting feature [47]. Miller and Cassady discussed how people of different ages and knowledge backgrounds make choices when given relevant task information (deciding which of two nutrition facts panels, presented side-by-side, was healthier) using eye tracking [48]. In essence, studies on the theme of patterns of decision making often took into consideration cognitive and developmental constraints. Thus in our study, we utilized eye-tracking to observe how players assigned their visual attention on different information stimulus when playing the function optimization game on computer screen.

2.4 Research Gap

In Section 2.1 we discussed that research on decision making in engineering systems design has been mainly focused on type of decision making or the rational decision methods given certain information. However, there exists a research gap on how diverse information stimuli are gathered by designers and how they cognitively assess various information sources in decision making. In Section 2.2 we showed that decisions can be considered as a function of decision makers’ cognitive styles or information processing styles, which are closely related to their visual attention patterns. Section 2.3 suggested eye tracking to be a promising tool to understand individuals’ decision making process involved with visual elements. Thus, in this behavioral study, we leveraged the insights provided by an eye tracking device in understanding how designers weigh different information stimuli to make decisions in engineering design contexts. These insights helped us identify the cognitive decision rules used by players and can assist to further the understanding of the decision making process. In the following section, the details of the design of experiment and the cognitive model are presented.

3 Design of Experiment and the Cognitive Model

3.1 Description of the Game

We adapt the function minimization game presented by Sha et al. [11] to study the decision making process of the participants. In [11], the game is used to study interactive decisions made by individuals in a multi-player setting. In this paper, the game is played in a single-player mode. The user interface of this game is shown in Figure 2.

In this game, the participants were asked to sample x values to find the minimum value of a randomly generated convex function. The participants were rewarded based on how close they came to the actual minimum of the function. Their profit (in dollars) was calculated as follows:

$$\text{Profit} = 5.5 - |x_{best} - x_{opt}| \quad (1)$$

where the x value corresponding to the minimum of the function is defined as x_{opt} and the x value sampled by the user resulting in the smallest distance to x_{opt} is termed as x_{best} . The entire process

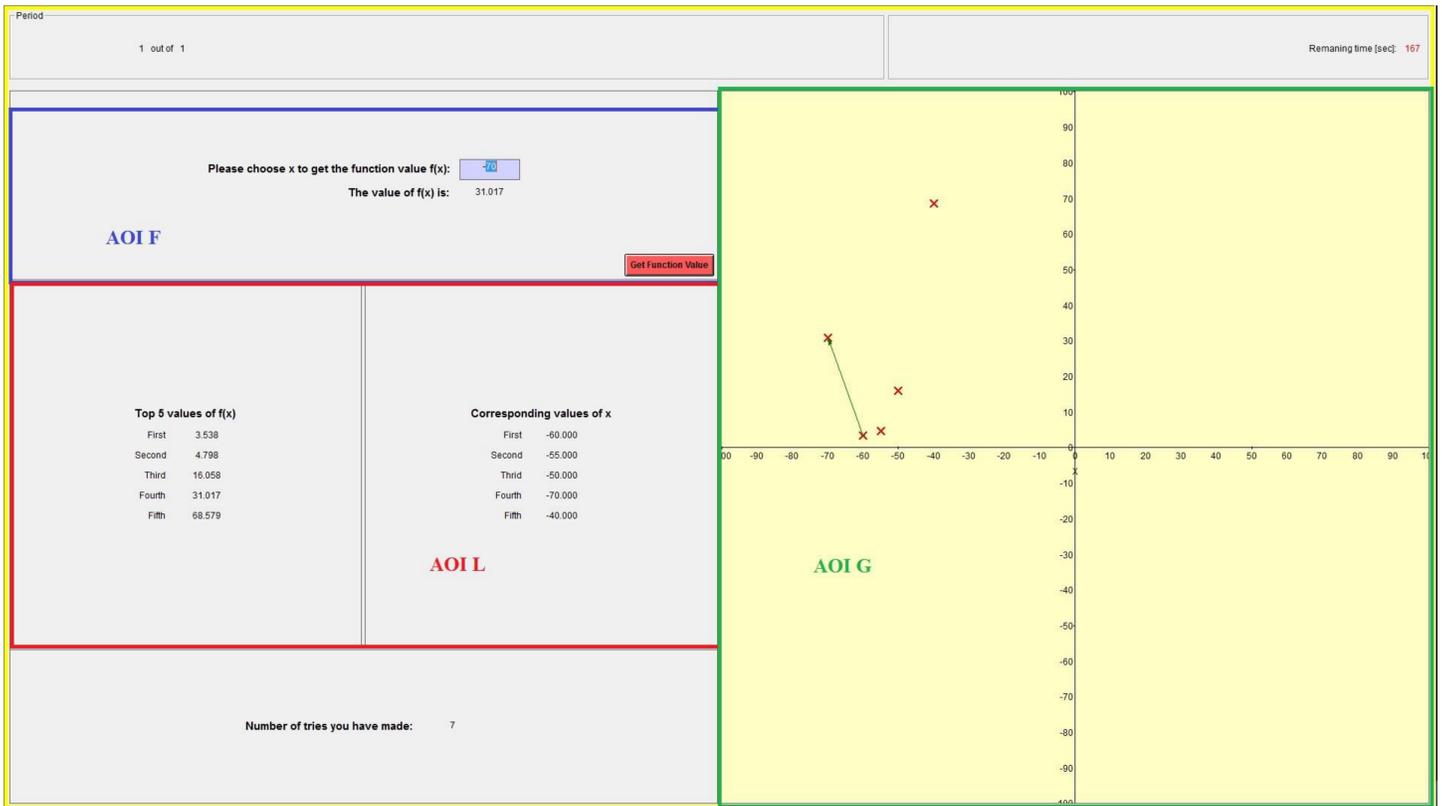


FIGURE 2. The user interface of the function minimization game and three Areas of Interests (AOIs)

of searching for the minimum till the profit calculation is defined as a period. The participants were asked to play for a total of 10 periods, and a different function $f(x)$ was generated for each period. The players were paid for two randomly selected periods. Therefore, their maximum profit was limited to $5.5 \times 2 = 11$ dollars. We randomly picked 2 periods out of 10 to ensure that the participants play all the 10 periods indifferently.

In the experimental design, there are two important and recurring decisions that a player makes to achieve his/her objectives. The player first decides the range in which he/she should focus the search and then decides the value of x to be utilized. This process is called a ‘try’. The player is asked to sample 10 times during each period. These decisions involve information gathering from the interface. We therefore chose the mentioned experimental design to study the impact of the information stimuli on various decisions made and the different strategies followed by the participants.

We divided the game interface into three principal Areas of Interests (AOIs), highlighted in Figure 2:

1. the function area where the user can input x values (AOI F),
2. the graph area where the user can visualize the function points searched (AOI G), and
3. the area which gives a list of the function value and x values searched (AOI L).

While a player is playing the game, the eye tracker is able

to record his/her eye gaze data within each AOI. The metrics mainly include the fixation time and fixation counts within each AOI, and the percentage time spent on each AOI (fixation time within one AOI divided by the whole period time). Based on the Eye-Mind assumption [34], these metrics correlate with players’ visual attention within each AOI positively. In other words, higher fixation time, more fixation counts and larger percentage time spent on one AOI indicate that a player paid more visual attention on this area.

3.2 The Cognitive Model

Considering the function optimization game in our study, players need to determine the best x values based on the provided numerical and graphical information regarding the x and $f(x)$ values. Players with different cognitive styles (such as verbalizers and imagers) would give different weightage to the numerical and graphical stimulus when playing this game [29]. Players’ weightage of visual attention on different information sources is assumed to indicate their preferred approaches to the search problem. Specifically, if a player is gazing more on the graph then the player is assumed to prefer a visual approach wherein he/she is creating a mental model of the function to look for the minimum. If a player is focusing more on the list then he/she is assumed to prefer an analytical approach wherein he/she is trying to utilize the exact values to improve the search range.

Figure 3 presents the overall cognitive decision process of the players in this game. Players need to determine the next x value based on the previously entered x values (usually chosen randomly for the initial two or three tries) and corresponding $f(x)$ values. This information is gathered either from the numerical values shown in the list area or from the points displayed in the graph area, or both. Players' differences in gathering information lead to their using different approaches for decision making [23]. We assume that the players either follow a curve fitting method or bisection method to make decisions about the x values.

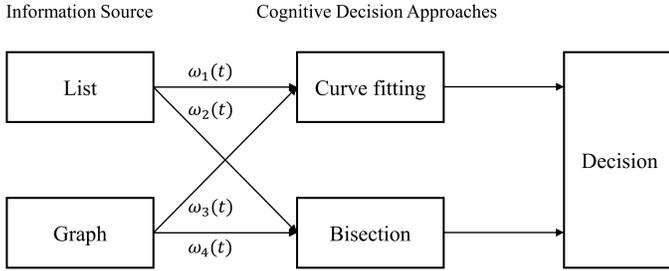


FIGURE 3. The overall cognitive decision process of this game

Specifically, we assume that if a player is looking at the graph, he/she is trying to visualize the curve to look for the minimum. Similarly if a player is looking at the data then he/she is trying to look for next x value which he/she believes to be the corresponding minimum. Players who weigh graphical information more are assumed to follow the curve fitting approach and are termed as *graphical* players. On the other hand, players who weigh list information more follow the bisection approach, and are termed as *numerical* players. The different weights associating the information source and the decision approaches are thus termed as $\omega_1(t)$, $\omega_2(t)$, $\omega_3(t)$, and $\omega_4(t)$. These weights are functions of time considering that the players' information gathering strategies can change over time.

Previous studies on problem-solving have shown that successful performers usually pay more visual attention on the critical areas of the visual stimuli than that of the unsuccessful performers [44]. Thus we expect well-performing players to focus more on the important areas of the user interface while playing this game. To test the significance of the information source in the game, i.e. the list and graph areas, we propose the hypothesis:

H1: The players who spend more time looking at the list and graph areas win greater profit.

The validity of this hypothesis would help confirm the importance of the list and graph areas as information sources in the cognitive decision process.

When using the bisection approach, players compare the relative magnitudes of previously obtained $f(x)$ values, and get the next x value by calculating the midpoint of the previous two x values. On the other hand, when using the curve fitting approach,

players would visually fit a curve in their minds based on the obtained x and $f(x)$ values, and get the best x value resulting in the minimum of the function. See Figure 4 for more explicit illustration of these two approaches.

In this game, accuracy is considered to have an inverse relation to the absolute difference between the x value tried and the x_{opt} . The quality of the solution is thus indicated by the accuracy. Players who follow the curve fitting approach are expected to have higher accuracy of the obtained x values. This is because curve fitting to a quadratic function mathematically requires three data points such that the minimum can be obtained after that. Therefore, ideally, four tries are required to find the minimum (including one try for submitting the final solution) if the participants perfectly follow a curve-fitting approach. However, the bisection approach is dependent on the range provided and the location of the minimum. This might require more than 4 tries to reach x_{opt} . Thus, graphical players are expected to converge to the x_{opt} values faster than the numerical players. This also means that the profit expected for the graphical players is higher given the way profit has been defined in Equation (1). To test whether the players who gave a higher weightage to the graphical stimulus primarily follow the curve fitting approach, we propose the following hypotheses:

H2a: Graphical players have a better solution quality.

H2b: Graphical players have a higher convergence rate.

The cognitive demand to players who follow the bisection approach is comparatively lower because of the more straightforward and easier calculation. These players are expected to decide the next x faster given that the number of search iterations is identical for all participants. Thus they would finish one period of this game in shorter time. To test the assumption that players who gave a higher weightage to the numerical stimulus primarily follow the bisection approach, we proposed the hypothesis:

H3: Numerical players spent less time during a period.

Testing hypotheses H2 and H3 would provide us insights about how players' weights on different information sources would impact their cognitive decision approaches and decision outcomes.

3.3 Experimental Procedure

Participants: Twenty graduate students from engineering schools at Purdue University were recruited to participate in the experiment. None of the participants knew about this game before and they were compensated 10 dollars on average for the participation. A quadratic function was used, but the participants were only informed that the function is convex.

Procedure: A Tobii X-60 (Tobii Technology AB, Danderyd, Sweden) eye tracking device was utilized to study the eye gaze patterns of the participants on the game interface and the participants were interviewed about their game-playing strategies after playing the whole game. The iMotions Attention Tool 5.3 software (iMotions Inc., Cambridge, MA) is used for analyzing eye gaze data.

Participants were briefed about the game, and then their eye

1	x_1	$f(x_1)$
2	x_2	$f(x_2)$
3	x_3	$f(x_3)$
4	$\frac{x_2 + x_3}{2}$	$f(\frac{x_2 + x_3}{2})$
...

Bisection Approach

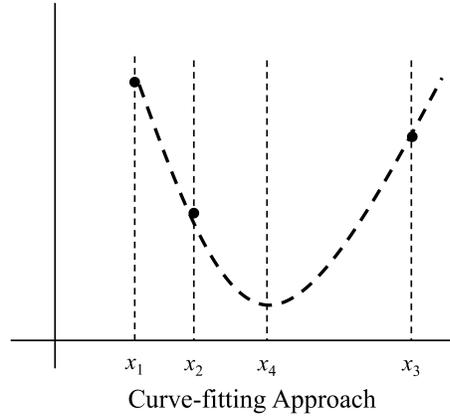


FIGURE 4. The bisection and curve-fitting approaches

gaze movements were recorded using the eye tracking device after which the game was started. Participants also needed to complete a survey at the end of the experiment. The survey was on the strategies that participants used in the game.

The participants took part in the study individually. They played the game for a total of ten periods, out of which, two periods were randomly selected to calculate their final payoff. This was done to ensure that participants play every period with same level of interest as they're not aware of the paying periods. The total sum from the two periods was then given to them as their profit. Since all participants in this experiment were completely unfamiliar with the function optimization game, the first two periods of each participant were considered as training tasks and these data were not taken into account.

4 RESULTS

4.1 Players' Overall Performance and Eye Gaze Data

A summary of players' overall gaming results and corresponding eye gaze data of each participant is given in Table 1. As an example, Player 1 spent on average 45.38 seconds and he/she obtained an average profit of \$4.99 for each period. On average, 28.13% of his/her playing time for each period was spent on looking at the function area (AOI F), 31.25% at the list area (AOI L) and 24.00% at the graph area (AOI G) respectively.

To test hypotheses H1 and H2a, the Pearson correlation coefficients ($\alpha = 0.05$) among players' gaming performance and corresponding eye gaze data were calculated. Important results are presented in Table 2. Here, AOI L+G represents the union of AOI L and AOI G, and AOI F+L+G represents the union of AOI F, AOI L and AOI G.

The results of Table 2 show that the average time spent by players does not affect their profit (corr. = 0.046, $p > 0.1$) which is calculated by their decision accuracy. Thus the absolute amount of time spent does not affect players' solution quality. We also observe that the players who spent more time looking at the list and graph areas tend to have a higher profit, but this trend is not significant (corr. = 0.42, $p = 0.065$). Thus, the hypothe-

sis H1 cannot be supported statistically from current results. In addition, the graphical players usually performed better in this game, i.e. getting higher profit and better solution quality (corr. = 0.505, $p = 0.023$). Thus, hypothesis H2a is supported by the experimental result.

However, we found that there is a strong correlation between players' average profit and their average percentage time spent on the sum of AOI F, L and G (corr. = 0.503, $p = 0.024$). This result implies that the function area may implicitly be used as another important information source in the decision-making process of this game. It is also interesting to see the negative correlation between players' average percentage time spent on AOI F and on AOI G (corr. = -0.563, $p = 0.01$). This negative correlation may suggest that players tend to allocate their visual attention mutually exclusively in the function area and the graph area.

4.2 Convergence of Participants' Input x Values in the Graphical and Numerical Periods

During the post-experiment interviews, all the participants indicated that they used a combination of the list and graph information for decision making. For example, a player could prefer to use graphical information for decision making in this period, but prefer the numerical information in another period. Thus, rather than simply categorizing the players into graphical and numerical players in an overall sense, we classified each period of each player into a graphical period or a numerical period based on the differences of a player's weight of visual attention on the list and graph areas. That is, if a player spent more time looking at the list area in one period, this period is considered as a numerical period. Otherwise, it is a graphical one.

Within each period, initially, say the first two or three tries, participants would usually choose the x values randomly to get a general idea about the range of the possible best x . Thus, we do not consider the first three tries in any period. After the first two or three tries, the participants try to narrow this range down according to the reasoning based on the results from either the list or the graph or both. It should be reasonable that the difference

TABLE 1. Players' overall gaming performance and corresponding eye gaze data

Player	Average time for each period	Average profit for each period (\$)	Average percentage time spent on AOI F (%)	Average percentage time spent on AOI L (%)	Average percentage time spent on AOI G (%)
1	45.38	4.99	28.13	31.25	24.00
2	102.38	5.49	29.50	21.63	28.38
3	71.50	5.17	20.75	23.25	25.38
4	102.33	5.01	30.50	41.00	7.83
5	67.88	4.69	30.25	40.00	2.88
6	53.33	5.49	36.33	18.83	17.33
7	89.50	5.49	22.50	34.50	22.63
8	54.50	5.42	31.50	9.83	19.67
9	73.00	5.43	30.38	28.38	16.13
10	152.29	4.65	23.86	42.86	4.29
11	125.57	5.26	18.71	25.00	29.71
12	62.25	5.49	43.00	27.75	7.88
13	131.13	5.46	28.25	37.88	20.38
14	73.75	5.35	32.88	38.13	4.13
15	140.63	5.45	18.88	42.63	26.88
16	98.00	5.49	29.75	37.50	16.50
17	96.63	5.44	27.63	35.00	19.38
18	81.67	4.56	34.17	40.50	2.00
19	137.29	5.48	49.29	22.86	10.00
20	85.86	1.73	36.00	25.43	1.43

TABLE 2. Pearson correlation coefficients between player's gaming performance and corresponding eye gaze data

Correlations	Pearson corr. coefficient	P-value
Aver. profit vs. aver. time	0.046	0.848
Aver. profit vs. Aver. percentage time spent on AOI G	0.505	0.023
Aver. profit vs. Aver. percentage time spent on AOI L+G	0.420	0.065
Aver. profit vs. Aver. percentage time spent on AOI F+L+G	0.503	0.024
Aver. percentage time spent on AOI F vs. AOI G	-0.563	0.010

between each try and the x_{opt} would converge to zero or a small number gradually as the participants become aware of the functional form. We calculate the absolute difference of the x values tried and the x_{opt} . We then perform an exponential regression to plot this difference vs. the number of tries based on the previous study by Sha et al. [11], which showed that the solution quality

is an exponential function of the number of tries. As the quality is expected to increase with each try, the absolute difference between the x values and the x_{opt} will decrease. The functional form is taken as $y = ae^{bx}$ where b is the convergence rate. The higher the absolute value of b , better is the convergence rate. In Figure 5, we plot the absolute values of the difference of the x

values tried and the x_{opt} for player 1 as an illustrative example.

The b value of the curve is obtained using least-square regression. This is done for each participant in each period. To test the hypothesis H2b, we perform a two-sample t-test to investigate the differences of the b values in the numerical periods (mean = -0.606 , SD = 0.493) and the graphical periods (mean = -0.658 , SD = 0.637). This difference is insignificant ($t = 0.5$, $p = 0.309$), thus the hypothesis H2b cannot be verified by the experimental results. Graphical players did not seem to have a higher convergence rate when playing this game.

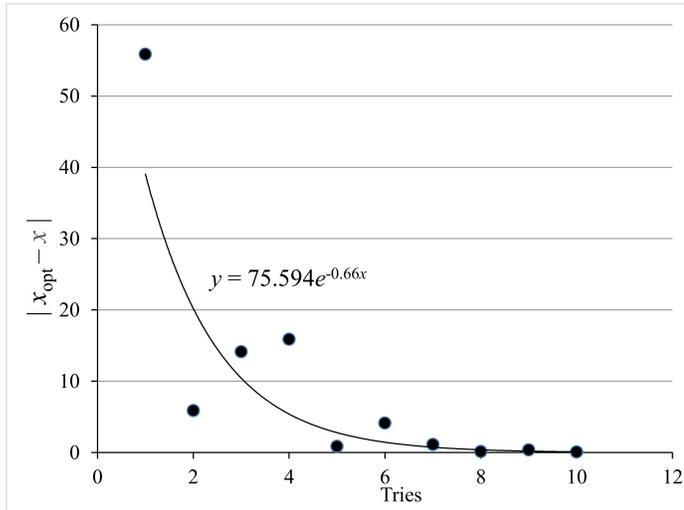


FIGURE 5. The plot $|x_{opt} - x|$ for each try by player 1 during period 7

4.3 Time Spent and Profit Obtained in the Graphical and Numerical Periods

To test hypothesis H3, we calculated the time spent and the profit obtained in each period for each participant. A two-sample t-test ($\alpha = 0.05$) was done to compare the time spent and profit obtained in the graphical periods and numerical periods, and the results are provided in Table 3.

We found that, there are no significant differences in the time spent for each period, irrespective of the player having more visual attention on the list areas or graph areas. Thus, the hypothesis H3 that the player observing the list area more spent less time during one period cannot be supported either. However, the profit differences between graphical and numerical periods are significant, which is consistent to the validity of hypothesis H2a.

Participants in our study also needed to complete surveys about their gaming strategies and preferences on information sources. It is interesting to find that player 3, 6, 8, 11, 15 17, 19 and 20 believed that graphical information was more helpful for them to determine the appropriate x values. Based on the eye gaze data shown in Table 1, only player 2, 4, 8 and 11 paid more

visual attention on the graph areas than on the list areas. This inconsistency may suggest that a person would not always be able to articulate his/her inherent cognitive styles in certain decision-making tasks [49] or they may not know that they are looking more at the list or the graph. In addition, it is possible that people found graphs more helpful because it provided a means for more quickly responding to the task than the text-based information [50], thus leading to less fixation times on the graphs. Players also indicated that they usually use a combination of approaches, i.e. the bisection method and curve-fitting method in playing this game, which could also explain the inconsistency.

5 CLOSING COMMENTS

Information gathering and processing is a crucial step in decision making process, thus it is necessary to understand the way information is gathered and weighed by designers to make decisions and the impact of their cognitive styles on such decisions. Think Aloud is a commonly used technique to understand how people solve problems or make decisions, but its main drawback is that it interferes with the thinking process of decision makers during certain short-time and highly concentrated tasks, and may not produce consistent results [49]. In this paper, we utilized an eye tracking device as a more objective and a non-invasive information gathering tool to capture players' eye gaze data to gain insights about their visual attention patterns and thinking processes.

We found that players' visual attention paid on the graph area of the game user interface positively correlated with their gaming performance, i.e., profit. This finding suggests that certain types of information stimuli could assist people in making better decisions. Also, players in graphical periods are found to earn more profit and have a better accuracy than in numerical periods, indicating that players' weights on different information stimuli could influence their decision results. This result is also consistent with Cleveland's finding that the human brain is more able to identify and comprehend relationships and patterns if data is encoded into visual forms [51]. Through this study, we show how the decision making process of an individual can be captured and understood using the eye tracking device as an effective tool.

On the other hand, the hypotheses regarding players' cognitive style models have not been supported by in this experiment. We fail to see that graphical players spend more time and numerical players get a higher convergence rate for each period. One possible reason is that in this game, participants did not receive balanced stimuli of numerical information and graphical information. Note in Table 3, the number of numerical periods ($N = 109$) is much greater than the number of graphical periods ($N = 38$). Some participants commented that they could not see the cross points shown in the graph area for the initial two or three tries, in which the $f(x)$ values were beyond the fixed range of the graph. Also, when they tried the eighth or ninth time, the cross points were too close to each other, so that the graphical information could not assist them in making decisions either. According to the interviews with the players, most of them indeed used the

TABLE 3. Comparison of time spent and profit between graphical and numerical periods

	Periods	N	Mean	SD	T-value	P-value	DF
Time spent for each period (s)	Graphical	38	89.60	35.30	-0.57	0.286	78
	Numerical	109	93.60	43.10			
Profit of each period	Graphical	38	5.39	0.32	2.80	0.003	134
	Numerical	109	4.99	1.39			

bisection approach when processing numerical information and the curve-fitting approach when processing graphical information. Although we expect the players who prefer to use graphical information to follow the curve-fitting approach primarily, these players were not able to rely on only one kind of information due to the unbalanced information stimuli. Therefore, even graphical players would also need numerical information for decision making, which could lead to the inconsistencies between our expectations and the players' actual decision behavior. Sojka and Giese confirmed that individuals with a high need for cognition prefer to process verbal information compared to visual information [52], which could also partially explain why 16 out of 20 players in our game paid more visual attention on the numerical area.

The future work includes a cognitive style test for participants (e.g., expanded Verbalizer-Visualizer Questionnaire [53]), a larger sample size, an in-depth analysis about the scan path of participants' eye fixations while playing the game, and other manipulations to the settings of the game, such as the competition mechanism and the improvement to the graphical user interface.

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