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A STUDY ON THE RELATIONSHIP BETWEEN DECISION-MAKING SPEED AND KANSEI THROUGH DATA VISUALIZATION

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ABSTRACT

Data visualization is the processing of data, directed at a person, content, and purpose, to simplify decision-making for the person. In practice, does data visualization affect people's decision-making time? In this study, we formulate questions using tables and graphs for three data groups, with varying amounts of information. Twenty subjects are asked to answer the questions from least to most of information, and the time taken to answer them is measured. Following the experiment, the attributes of the subjects, including gender, age, occupation are obtained via a questionnaire. The experiment reveals that as information increases in the tabular format, the answering slows proportionally. In contrast, in the graph format, the responses do not slow down proportional to the increase in information. The relationship between the subjects' attributes and the speed of answering is determined and some significant differences are found. Six patterns of relationship between the answering time for the tables and graphs are obtained. Subsequently, the relationship between these attributes and "change of flow from data to action (hereinafter called "the decision-making process")" are examined in Kansei engineering, and the data visualization is found to be potentially effective at speeding up the decision-making process.

Keywords: *data visualization, decision-making, judgement, visualization*

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1 INTRODUCTION

In the past 20 years, the amount of information produced by humans has accelerated, and is believed to have increased 5,000 times (Japanese Ministry of Economy Trade and Industry, 2011). Companies that can analyze the information, decide based on that data, and quickly perform a plan-do-check-act (PDCA) cycle can advance further. Data visualization is used to represent information using computers to create appropriate and effective graphs and charts. It is designed to speed up the PDCA cycle by simplifying decision-making for viewers. It does so by becoming aware of people and purpose (Berinato, 2016). Particularly in business, data visualization is a powerful tool for decision-making. The purpose of this study was to determine how decision-making speed changed when using data visualization; how much it changed when more information was available. Also it aimed to verify whether the speed is related to attributes, such as gender, age, occupation, and academic background, etc. We used multivariate analysis of the data to arrive at conclusions (Blocher et al., 1986). Finally, we considered the influence of data visualization on human decision-making speed and sensitivity, according to the decision-making process (Shiizuka, 2011) proposed in Kansei Engineering.

2 LITERATURE REVIEW

Business intelligence (BI) has emerged as a system that collects data and makes them visible and understandable to people. Additionally, it is a system that creates support information for decision making for a variety of user applications (Jones, 2011). As an executive information system, the BI tool is a system wherein information is visualized for being easily understood by management (Lauer & O'Brien, 2020). It collects raw data and transforms it into valid information to drive enterprise business performance and provide strategic, tactical, and operational insights for decision-making. (O'Brien & Lauer, 2018). Applying data visualization to the output of BI tools in the form of tables and graphs, and to make them more understandable to subjects can have a significant impact on decisions (Moere et al., 2012). The format in which the graphs are displayed may be recognized to affect decision-making (Borkin et al., 2013; Dragicevic & Jansen, 2018; Lee et al., 2019). It has been shown that compared to plain text, graphs help make better use of obtained information and grant deeper insights (Iwatsuki, 1998). Graphs enable the construction of an adequate situation model and facilitates understanding text-comprehension (Iwatsuki, 2006). In addition, the visual embellishment of tables and figures has a significant and positive impact on the speed of memory recall as people judge when tables and figures are embellished (Borgo et al., 2012). In Kansei engineering, with respect to the decision-making process, it proceeds in the following sequence: data, information, knowledge, wisdom, and action. When the user receives consolidated information and integrates information in his or her mind and deeply understands the knowledge, the knowledge becomes wisdom, which results in the final action (Shiizuka, 2011). There are several studies on how people make decisions when purchasing products (Ishida et al., 2005), and what kind of images in advertisements motivate people to purchase goods (Tsuchiya et al., 2003). However, few experiment has quantitatively shown how graphs and charts affect the speed of human decision-making. Also studies on the relationship between decision-making speed and attributes of human have few performed.

3 METHODS

The experimental process is shown in Figure 1. Subjects were asked to answer questions containing tables and graphs. Herein, the questions with data visualization are referred to as graph format, and those without data visualization as tabular format. The primary data of the question had one column, the secondary data two columns, and the tertiary data three columns. As the number of columns increased, the amount of information increased, and so did the difficulty level (Figure 2). The durations to answer the questions were measured. There were 20 questions of the primary and the secondly and the tertiary were each 10 questions in all.

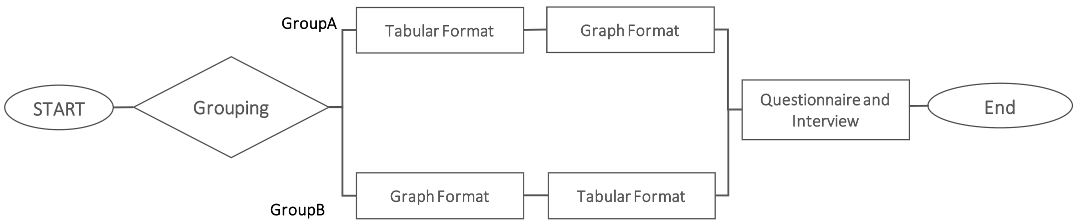
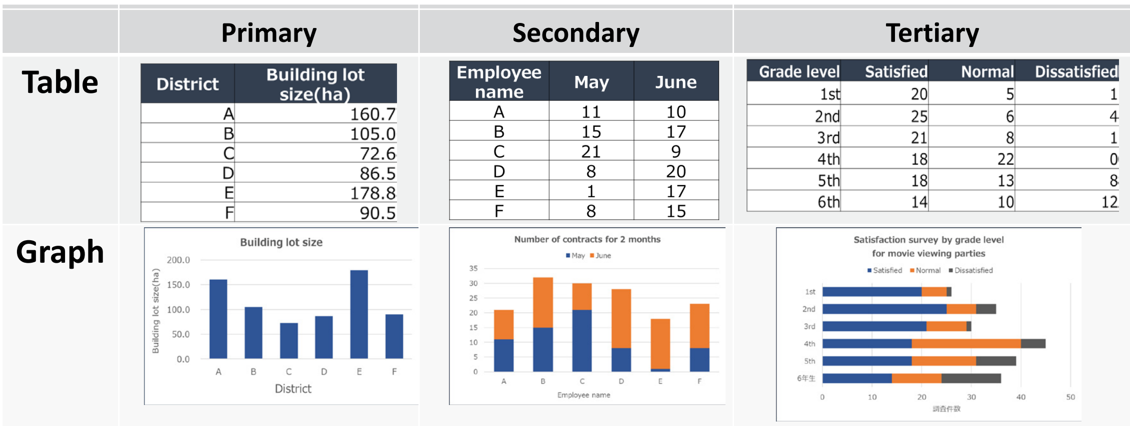


Figure1. Experimental process



District	Building lot size(ha)
A	160.7
B	105.0
C	72.6
D	86.5
E	178.8
F	90.5

Employee name	May	June
A	11	10
B	15	17
C	21	9
D	8	20
E	1	17
F	8	15

Grade level	Satisfied	Normal	Dissatisfied
1st	20	5	1
2nd	25	6	4
3rd	21	8	1
4th	18	22	0
5th	18	13	8
6th	14	10	12

Figure 2. Example of questions in tabular and graph format

The questions in the experiment were designed to be answered by those with arithmetic knowledge up to elementary-school level (according to the elementary-school curriculum guidelines set by the Ministry of Education, Culture, Sports, Science and Technology of Japan). An example question was provided at the beginning of the question text, so that all the subjects could answer. The subjects were divided into 2 groups. Group A answered the questions first in tabular format, and then in graph format. Group B answered the questions first in graph format, and then in tabular format. After the experiment, the subjects were presented with a questionnaire, and interviewed to analyze the relationship between the speed of answering duration and attributes. Twenty-two subjects participated in the experiment, but 2 subjects had incomplete experimental data. Therefore, data from 20 subjects were included in the study (Table 1).

Table 1. Subject list (*two subjects excluded due to inadequate data)

Group	No. of subject	Gender	Age	Occupation	Technical background	Final education
A	1	F	40s	Self-employed	n	Senior high school
A	2	M	40s	Executive	y	University
A	3	M	20s	Student	n	University
A	4	F	20s	Unemployed	n	University
A	5*	M	30s	Self-employed	n	University
A	6	M	30s	Office worker	n	College
A	7*	M	30s	Self-employed	n	Senior high school
A	8	F	30s	Office worker	n	University
A	9	M	30s	Public servant	n	University
A	10	M	30s	Office worker	y	University
B	11	M	40s	Office worker	y	Graduate school
B	12	M	30s	Office worker	n	University
B	13	M	20s	Office worker	n	Graduate school
B	14	M	30s	Self-employed	n	University
B	15	M	30s	Self-employed	n	Senior high school
B	16	F	30s	Office worker	n	Vocational school
B	17	M	50s	Self-employed	n	Senior high school
B	18	F	30s	Office worker	n	University
B	19	M	30s	Free lance	n	University
A	20	M	40s	Office worker	y	Graduate school
A	21	M	50s	Office worker	n	Graduate school
B	22	M	20s	Office worker	n	Graduate school

4 RESULTS

Each subject's average duration of answering were summarized.

4.1 Speed results for answering

As described in the experimental process, we considered the counterbalance for the 2 groups that affects the answering time. Subsequently, non-parametric tests were conducted to analyze the 2 groups and answering durations. The results revealed that the asymptotic significance probability (two-sided) was 0.254, which implied that the order of answering the questions did not affect the answering duration. This confirmed the validity of the experimental method. (Tables 2 and 3). The speed of answering was categorized according to the amount of information and the format, such as the primary table and primary graph, etc. The changes in the average duration of answering are presented in Table 4 and Figure 3. As the amount of information increased from primary, to secondary to tertiary, the difference in answering durations increased between tabular and graph formats.

Table 2. Changes in average time to answer per question for the 2 groups (Table = T, Graph = G)

Format	Primary (T)	Primary (G)	Secondary (T)	Secondary (G)	Tertiary (T)	Tertiary (G)
Average time to answer of group A	4.7	3.8	13.2	6.4	19.2	7.5
Average time to answer of group B	4.2	3.4	10.2	6.2	15.4	6.7

Table 3. Test statistic as related to two group and response time

Test statistic	Average time taken to answer
the asymptotic significance	0.254

a. Grouping variables: Experiment order

Table 4. Changes in average time to answer per question (Table=T, Graph=G)

	T	G
Primary	4.7	3.8
Secondary	12.2	6.6
Tertiary	18.1	7.4

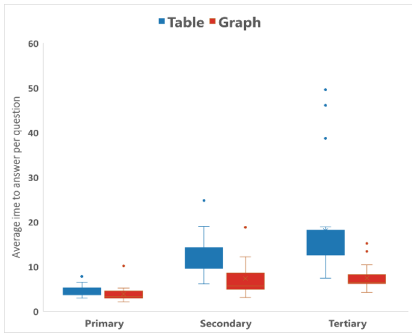


Figure 3. Changes in average answering time

4.2 Results of questionnaire and interview

A total of 13 questions were presented, including gender, age, occupation, type of business, type of work, previous work experience, final education, background is technical or not, whether they had studied how to create graphs and charts in the past, whether they used graphs and charts in their daily lives, which ones they often used, and their feelings about the experiment. Subsequently, the factors influencing the speed or duration of answering was investigated. First, non-parametric tests were conducted to analyze factors, such as gender, age, occupation, and answering time. The result was not significantly different from the answering time, except for the level of difficulty and question format (Table 5). No significant difference was found for occupation, but there was a significant trend. Next, a two-way analysis of variance (ANOVA) was conducted to examine the interaction between the significant differences in answering duration. As shown in the non-parametric test, significant differences were found between difficulty, method, and interaction (Table 6). However, as we observed a large change in answering time between company-executive, self-employed, and other occupations, we decided to create a new column called “Occupation 2” and perform the test again. In Occupation 2, all occupations except company-executive and self-employed were classified as other. The results exhibited a weak correlation (Table 7).

Table 5. Non-parametric test analysis of questionnaire items

Factor	p value
Gender	p = 0.626
Age	p = 0.129
Technical	p = 0.970
Final education	p = 0.202
Occupation	p = 0.67
Difficulty	p = 0.000
Format	p = 0.000

Table 6. Two-way ANOVA results for the interaction difficulty with formality and job type

Factor	p value
Difficulty	p = 0.000
Format	p = 0.000
Occupation	-
Difficulty*Occupation	p = 0.662
Difficulty*Format	p = 0.000

Table 7. Two-way ANOVA results for question difficulty for occupation 2

Factor	p value
Difficulty	p = 0.000
Occupation 2	p = 0.526
Difficulty*Occupation 2	p = 0.083

Although this is only a trend, as the amount of information in the tabular format increased, the response duration increased proportionally. However, in the graph format, the duration did not increase proportionally with increase in the amount of information. With such an increase and compared to others, company-executive and self-employed subjects showed greater differences in response durations between tabular and graph formats. In a follow-up interview, the company executive and the self-employed person were asked why it took them longer to answer the questions in tabular format than in graph format. The self-employed said, “Because I keep accounting books, I dared to be calm and took my time with the numbers in the tabular format.” and the company executive said, “In the case of the tabular format, I looked at all the lines to avoid answering the questions incorrectly.”

4.3 Question format and response-time patterns

The answering durations of the 20 subjects were analyzed according to the question format and difficulty level. The results showed 6 patterns (Table 8, Figure 4).

Table 8. A-E grouping factors and applicable subjects

Pattern	Format	Time to answer from Primary to Secondary	Time to answer from Secondary to Tertiary	Applicable subject number
A-1	Table	Become longer	Become longer	9, 15, 17, 21, 22
	Graph	Become longer	Become longer	
A-2	Table	Become longer	Become longer	11, 18, 19, 20
	Graph	Become longer	Become longer	
B	Table	Become longer	Become longer	1, 6, 12, 13, 14
	Graph	Become longer	Become shorter	
C	Table	Become longer	Become longer	2, 8, 10
	Graph	Become shorter	Become longer	
D	Table	Become longer	Become shorter	3, 4
	Graph	Become longer	Become longer	
E	Table	Become longer	Become shorter	16
	Graph	Become shorter	Become longer	

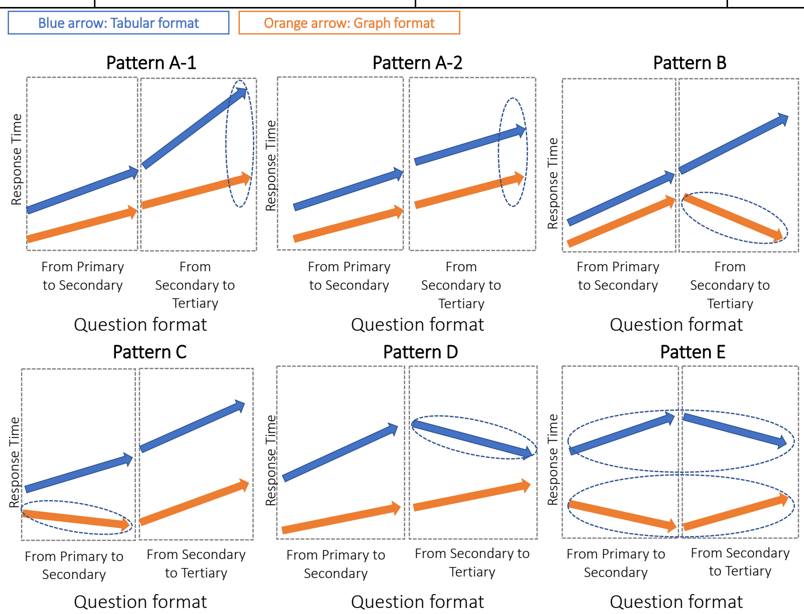


Figure 4. Variation of the answering time for groups A-E according to question format and difficulty level

First, Pattern A revealed that as the amount of information increased, answering duration increased steadily in both, tabular and graph formats. In Pattern A-1, the difference in the duration from secondary to tertiary between the tabular and graph formats was larger than from primary to secondary. Five subjects belonged to this group. Pattern A-2 also exhibited a steadily increasing response duration, but its difference from secondary to tertiary order of tabular formats was smaller. It included 4 subjects. In Pattern B, the duration increased steadily in the tabular format, but in graph one, it decreased as the information increased from secondary to tertiary. This included 5 subjects. Pattern C revealed an increasing duration in the tabular format, but a decreasing one in graph one, only for the first- and second-order questions. This included 3 subjects. Pattern D involved a tabular format, in which the answering duration shortened with increase in information amount from secondary to tertiary. However, in the graph format, the duration increased for both, primary-to-secondary and secondary-to-tertiary, as the time increases steadily. This included 2 subjects. In Pattern E, including 1 subject, the answering duration shortened with increase in information, from secondary-to-tertiary order in tabular format. However, in graph format, the response slowed from secondary-to-tertiary order. Non-parametric tests were conducted to analyze the relationship between attributes of subjects and 6 patterns. There was significant difference in graphing experience only in pattern A-2. In others, the difference was not significant in terms of the p-values for attributes (Table 9).

Table 9. Significant differences for Patten A-E group *Pattern E is excluded because of one subject

Pattern	Gender	Age	Occupation	Technical	Education Background	Graphing experience
A-1	-	-	0.39	0.59	0.39	-
A-2	0.83	-	0.059	0.056	-	0.04
B	0.63	-	0.289	-	0.472	0.982
C	0.63	0.86	0.86	0.63	-	0.188
D	0.83	-	-	0.83	-	0.83

5 DISCUSSION

The results of the experiment indicate that the decision-making speed, when looking at data in tabular and graph formats, may be related to occupation. Six patterns of response duration of 20 subjects were analyzed according to the question format and difficulty level. Next, we discuss the relationship between data visualization and the decision-making process (Shiizuka, 2011). Data change into information when they are organized into a meaningful form, presented in an appropriate method, and transmitted within their surrounding context. Data is delivered to a receiver by a sender, through visual information with graphs as a meaningful form. That establishes communication by explicit knowledge. Data visualization shortens the interpreting duration, thus potentially speeding up the transition from knowledge/wisdom to action and enabling decisions. This is represented using the decision-making process, where the x-axis is the Subjective and the y-axis is the Objective (Shiizuka, 2011). In addition, the z-axis is the rate of progress to decision-making. The length of the line is the time taken. The green line indicates the movement with data visualization, and the red line indicates the movement without it (Figure 5). When data visualization is utilized, the progress from data to information is linear, as opposed to the progress without data visualization. When entering the non-verbal area from information, it takes much time to understand the information if there is little visual information, such as in a tabular format. However, the graph format processed by data visualization facilitates decision-making by stimulating the five senses that make knowledge and wisdom function. It suggests that subjects' take less decision-making time when they see graphs processed by data visualization. Thus, data visualization effectively speeds up the decision-making process. For example, a company's management must make optimal decisions considering various factors with knowledge and wisdom. Therefore, to make data actionable quicker, despite the recent enormity of information, we believe that visual stimulation will be effective (Figure 6). Subsequently, we examined the relationship between each flow and data visualization on the receiver side in the non-verbal area. In this study, since the subjects were only allowed to choose their answers from the questions, there was no difference in the action. Therefore, change in response duration was defined as the action. We confirmed 6 patterns of Kansei among the 20 subjects. When analyzing their answering times in tabular and graph formats, with increasing amount of information, we could not find significant differences among the 6 patterns. As Shiizuka states, this could be because knowledge and wisdom are acquired by each individual before proceeding to action and they overlap as a spectrum (Shiizuka, 2011). Therefore, it was difficult to isolate and identify a single component

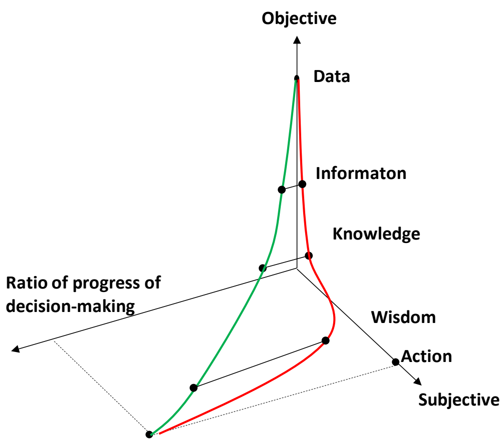


Figure 5. Change flow from data to action (decision-making) with the rate of progress of decision-making added as the z-axis

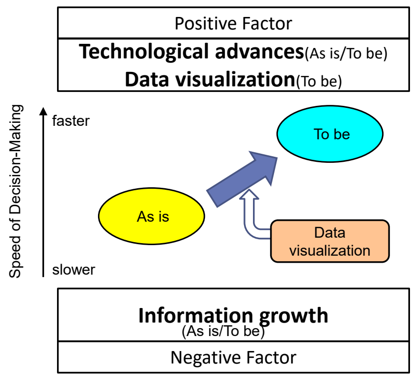


Figure 6. Data visualization driving speed of decision-making

6 CONCLUSION

In this study on the relationship between data visualization and answering time, the following conclusions were drawn. As the amount of information in the graph format increases, the answering time does not increase proportionally. The relationship between the decision-making process and data visualization revealed that: the graph format with data visualization shortened answering duration towards "information" directly; the rate of progress of decision-making, from "knowledge" to "action", was accelerated by data visualization; and 6 patterns of durations emerged. The patterns were defined as Action and analyzed. It revealed no significant difference between subjects attributes and the 6 patterns due to the spectrum. In future, we can increase the sample size, ask each subjects to repeatedly answer different questions, and examine the attributes in more detail.

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