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Human Performance and Heat Map Entropy in System State Judgment Task using a Visual Interface Screen

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Abstract

The purpose of this study was to identify the relationship between human performance and heat map entropy in a system state judgment task through the visual interface screen. A prototype of an EID-based accident response support system was used as the visual interface screen for the experiment. Sixteen subjects performed an experiment in which the system state was judged based on the problems presented by the experimenter through the visual interface screen. The experimental results confirmed that the heat map entropy increased as the time to judge the system state increased. In addition, it was confirmed that the heat map entropy of cases that did not correctly judge the system state was significantly greater than that of cases that correctly judged the system state. It was found that a close relationship existed between the performance of judging the system state from the visual interface screen and heat map entropy. This means that it can predict human performance based on heat map entropy. Therefore, heat map entropy can be used to evaluate the suitability of the visual interface design.

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1. Introduction

Humans receive more than 80% of their information through a visual interface in a human-machine system.[1] Therefore, eye-tracking studies have been conducted to evaluate the visual interface of a human-machine system.[2] In general, eye tracking analysis includes a quantitative method that uses basic indicators, such as fixation counts and duration, and a qualitative method that utilizes visualization patterns, such as gaze plots and heat maps.[3] Quantitative analysis of eye tracking using fundamental indicators is effective for analyzing the components or fixation time of the user's gaze, but it is not easy to interpret the overall aspect of gaze movement. On the other hand, there is a problem in that it is difficult to quantitatively analyze the eye tracking in the analysis using the visualization pattern of the gaze movement. Therefore, gaze entropy, which introduces entropy to the distribution of gaze movement, has been used in various studies to evaluate visual interfaces.[4,5] Ahn *et al.* studied the relationship between the stereoscopic level of the screen and the heat map entropy,[6] while Fajnzylber *et al.* conducted a study to find out how the user's gaze characteristics change on a non-realistic rendered 3D screen.[7] Jordan and Slater used entropy to investigate the effect of stress factors on users' gaze characteristics in a virtual reality environment.[8] Gu *et al.* used gaze entropy to measure the aesthetics of web pages quantitatively.[9] Hooge and Camps analyzed consumers' gaze movement characteristics using gaze entropy to go to the brand logo when viewing advertisements.[10] Gotardi *et al.* employed gaze entropy to determine how anxiety affects drivers' gaze characteristics while driving.[11] Jungk *et al.* analyzed the correlation between the task failure rate and gaze entropy for ecological display, profilogram display, and trend display that monitor a patient's hemodynamics.[5]

Gaze entropy includes Shannon entropy, dwell time entropy, Markov entropy based on the gaze plot,[12] and heat map entropy based on the heat map.[3] Shannon entropy is calculated based on the fixation counts in the area of interest.[13]

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Unlike Shannon entropy, the dwell time entropy is calculated based on the fixation duration for the area of interest. Markov entropy is calculated based on the fixation counts in the area of interest and the number of movements between areas of interest using a Markov chain model.[14] Additionally, the heat map entropy is calculated based on the gaze intensity of the visual elements.[15]

Unfortunately, few experimental studies have been conducted on the relationship between task performance and gaze entropy in visual interfaces. Lee *et al.* compared the gaze movement characteristics of student pilots and professional pilots during aircraft landing using gaze entropy.[16] Professional pilots with high performance showed significantly lower gaze plot entropy for the airplane instrument panel than student pilots. Lee *et al.* studied the correlation between situation awareness and gaze entropy in an emergency accident at a nuclear power plant.[17] It was confirmed that the higher the performance of situation awareness, the lower the gaze entropy. Merwe *et al.* studied whether gaze entropy could be a criterion for judging situation awareness in in-flight situations. When an error occurred, the pilots' gaze entropy increased. Pilots that failed the task showed low situation awareness and high gaze entropy.[18] Bhavsar *et al.* used gaze entropy to analyze the gaze characteristics of success and failure groups for tasks in a chemical industry control room. The successful group showed lower gaze entropy than the unsuccessful group.[19] Wu and Cha, through a study on the relationship between eye-tracking metrics and perceived workload in robotic surgical skills training, confirmed that gaze entropy increased as the perceived workload increased.[20] Di Stasi *et al.* studied the relationship between task complexity and gaze entropy in a virtual simulation environment and found that gaze entropy increases linearly as task complexity increases.[21] Diaz-Piedra *et al.* confirmed that gaze entropy tended to decrease as flight complexity increased through experiments using a flight simulator.[22]

Looking at the relationship between task performance and gaze entropy from the results above, it can be seen that gaze entropy tends to decrease as task performance increases. However, in a study by Dias-Piedra et al., gaze entropy decreased when task complexity increased.[22] Since an increase in task complexity causes a decrease in task performance, gaze entropy also decreases when task performance decreases. It cannot be conclusively stated that gaze entropy is low when the task performance is high. There has been no study on the relationship between task performance and gaze entropy for information-processing tasks in visual interfaces. Therefore, further research is needed to suggest the possibility of using gaze entropy to evaluate the suitability of visual interface design.

Looking at the results of previous studies using gaze entropy in visual interfaces, plot-based gaze entropy is an effective method when the user's area of interest can be clearly defined; otherwise, heat map entropy is effective.[9] Because a general visual interface screen has many components, it is meaningless to classify only the characteristic parts as areas of interest. In such cases, heat map entropy can be effectively utilized. Endsley and Jones stated that because the judgment of the system state directly affects the human cognitive process, it is possible to know whether the interface system provides correct information through the performance of the state judgment on the visual interface.[23] This provides a basis for evaluating the suitability of the visual interface design based on the performance of the system state judgment task. By studying the relationship between the performance of the system state judgment task and the heat map entropy, it is possible to determine whether the heat map entropy can be used as an indicator to evaluate the suitability of visual interface design. Therefore, this study attempted to experimentally identify the relationship between task performance and heat map entropy to judge the system state through a visual interface screen.

2. Methods

2.1 Heat map entropy

In this study, the accident response support system screen of a nuclear power plant designed using Ecological Interface Design (EID) was used for the experiment. Because it is difficult to designate and analyze only specific components as areas of interest in an EID-based accident response support system, heat map entropy was used as a measure of gaze movement analysis.

Because the heat map has the form of a Gaussian distribution from the point where the gaze stays the longest to the point where the gaze stays the least, entropy is calculated using Gaussian distribution.[17] Assuming that the gaze follows a Gaussian distribution centered on a specific pixel (x_f, y_f), the continuous probability distribution of the gaze forming the heat map is expressed by the following Equation (1).[15]

$$f_{XY}(x,y) = \frac{1}{2\pi\sigma^2} exp - \left(\frac{(x-x_f)^2+(y-y_f)^2}{2\sigma^2}\right) \quad (1)$$

In Equation (1), σ is the standard deviation, which is the visual angle in eye tracking, and the range of pixels that the user can recognize when viewing a screen. If multiple fixation distributions are formed on the screen, it is necessary to assign weight to the fixation distribution and express it as one continuous probability distribution, as follows Equation (2):

$$\tilde{f}_{XY}\,(x,y) = \sum_{f=1}^{f_{num}} d_f \times \frac{1}{2\pi\sigma^2} exp - (\frac{(x-x_f)^2+(y-y_f)^2}{2\sigma^2}) \quad (2)$$

Here, f_{num} is the number of fixations and d_f is the weight of each fixation distribution. The heat map entropy can be calculated using this joint probability distribution function.[9]

$$H = -\sum_{xy} \widetilde{f_{xy}}\,(x,y) \cdot log\tilde{f}_{xy}(x,y) \quad (3)$$

The heat map entropy was calculated using Python software. The following Python code was used to calculate the heat map entropy.

```
# Defining a Heatmap Combined Probability Distribution Function with Weights
def entropy_calc(data):

# Total number of pixels, X and Y
#     NROW=1280
#     NCOL=1024

    a = range(0,10280,1)
    b = range(0,1024,1)

    # Calculate Weighted Values 'df'
    total_duration = sum(data['duration'])
    alpha_lst = data['duration']/total_duration
    x_f_lst = data['Fixation point X']
    y_f_lst = data['Fixation point Y']

    ent_val = 0
    for x in a:
        for y in b:
            tmp_val = 0
            for i in range(len(data)):
                alpha = alpha_lst[i]
                x_f = x_f_lst[i]
                y_f = y_f_lst[i]
                tmp_val += alpha*g_dist(x+1,y+1,x_f,y_f)

            ent_val += (-1 * tmp_val) * np.log2(tmp_val)

    return ent_val
```

2.2 Experiment

2.2.1 Participants

Sixteen undergraduate (male 8, female 8) engineering students with no prior experience in the accident response support system of the nuclear power plant participated in the experiment. Their average age was 22.3 years (SD=1.5 years). Participants were required to have normal or corrected to normal vision in both eyes.

The reason why college students were selected as subjects were to match the degree of understanding of the system to the same level as the subjects. Another reason is the ease of recruiting participants. To increase the fidelity of participating in the experiment, the subjects were paid \$20 as an experimental participation fee.

2.2.2 Experiment equipment

In this experiment, the visual interface prototype of the accident response support system implemented by the EID method was used. EID is a design method for workers to easily and quickly solve problems by visualizing in an easy-to-understand way the relationships between constraints on the work domain and the various and complex levels of information related to them.[24-28] EID is an interface design approach explicitly introduced for complex sociotechnical, real-time, and dynamic systems. It has been applied in various domains, including process control, aviation, and medicine.[26,28] EID differs from some interface design methodologies like user-centered design (UCD) in that the analysis focuses on the work domain or environment rather than on the end-user or a specific task.[29]

For the experiment, a laptop with a prototype installed was used. An additional monitor was connected to the laptop to display the visual interface screen for the experiment. The accident response support system prototype consisted of a main screen and four lower screens. Fig. 1 shows the main screen and temperature control screen of the accident response support system used as the experimental simulator.

This experiment utilized Tobii Pro Glasses 2 as an eye-tracking system. The Tobii Pro Glasses 2 is a recent head-worn eye tracker that is commonly used across a range of studies. Tobii Pro Glasses 2 allows researchers to capture truly objective and deep insights into human behavior in any real-world environment.[30,31] Tobii Pro Glasses 2 consists of a head unit, a recording unit, and controller software. The gaze sampling frequency of Tobii Glass 2 is 100 Hz. Tobii Pro Glasses 2 was calibrated individually for each participant to collect accurate eye-tracking data. Participants were asked to make themselves comfortable before the calibration and the session to ensure they would stay within these bounds. To analyze the gaze movement, it was analyzed that saccade occurred when the eye movement angle was more significant than 100 degrees in 1sec, and fixation occurred when the gaze stayed at a specific point for more than 60ms.

2.2.3 Experimental scenarios

In this experiment, three types of problems were developed to judge the system's state from a visual interface screen. The first problem type is observing the change in an indicator and judging its state (e.g., how does the value of the steam generator (SG) 1 level change?). The second problem type is judging an indicator that meets specific conditions (e.g., which power equipment requires maximum demand?). The third problem type is assessing an indicator that shows a specific change in a certain condition (for example, after a while, both demineralized water transfer pumps will be stopped. Which water route will become unavailable in this case?). A total of 24 problems were developed, with 8 for each problem type. Subsequently, 17 scenarios were developed for this experiment. Scenarios were developed so that the indicators of the system could change at appropriate times according to the three types of tasks that judge the system's state.

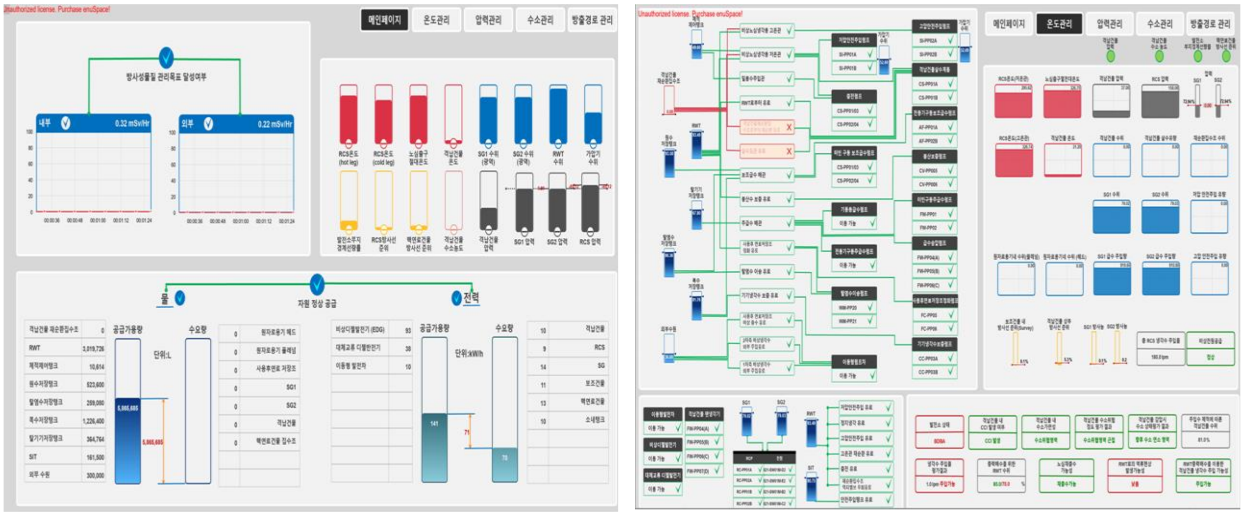


Fig. 1 Interface screens of the simulator for the experiment.

2.2.4 Experiment procedure

Before starting the experiment, the subjects were educated on the visual interface screen, the meaning of the indicator, and the experimental scenario and were then trained on the experiment. During the training, ten problems of the judging system state were presented to the subjects, and the training ended when the correct answers were given.

Among the 17 scenarios developed for the experiment, five were selected for the experiment. The system indicators on the visual interface screen change according to the selected experimental scenario. During the experimental scenario, the experimenter presents one of three problem types to the subject at an appropriate time. At this time, the subject should present the correct answer to the problem as quickly as possible while looking at the interface screen. The experiment was conducted 5 times for each problem type.

The experiments were conducted in a quiet laboratory. The subjects wore an eye tracker during the experiment, and the distance between the subject and the monitor was 60 cm.

3. Results and discussion

3.1 Judgment time and heat map entropy according to problem type

To verify the relationship between judgment time and heat map entropy, judgment time and heat map entropy were first analyzed according to the problem type. Fig. 2 shows the means and standard deviations of the judgment time (a) and heat map entropy (b). Fig. 2(a) shows that problem type 1 had the longest judgment time, followed by type 3, while type 2 had the shortest judgment time in both cases, including and excluding incorrect answers. The difference in judgment time according to problem type was statistically significant at a significance level of 0.05 in both cases, including (F=12.610, p=0.000) and excluding (F=11.846, p=0.000) incorrect answers. Looking at the judgment times when including and excluding incorrect answers, the judgment time when excluding incorrect answers tended to be slightly shorter than when including incorrect answers.

In the graph in Fig. 2, the error bars represent standard deviations. The large error bar in the case of including incorrect answers for the type 1 task occurred because some subjects who made incorrect judgments of the system state showed a long judgment time.

Figure 2(b) shows that problem type 1 had the most significant heat map entropy, followed by type 3, with type 2 having the smallest heat map entropy in both cases, including and excluding incorrect answers.

The difference in heat map entropy according to problem type was statistically significant at a significance level of 0.05 in both cases, including (F=7.695, p=0.001) and excluding (F=6.039, p=0.003) incorrect answers. Looking at the heat map entropy of the cases of including incorrect answers and excluding incorrect answers, the heat map entropy of the case of excluding incorrect answers tended to be slightly lower than that of the case of incorrect answers.

From the analysis results, the order of magnitude of the mean heat map entropy according to the problem type was the same as the judgment time, and the differences also showed the same statistical significance. This result shows a close relationship between the judgment time and the heat map entropy.

3.2 Judgment time and heat map entropy according to the success or failure of judgment

In the analysis of the judgment time and heat map entropy according to the problem type, it can be seen that the judgment

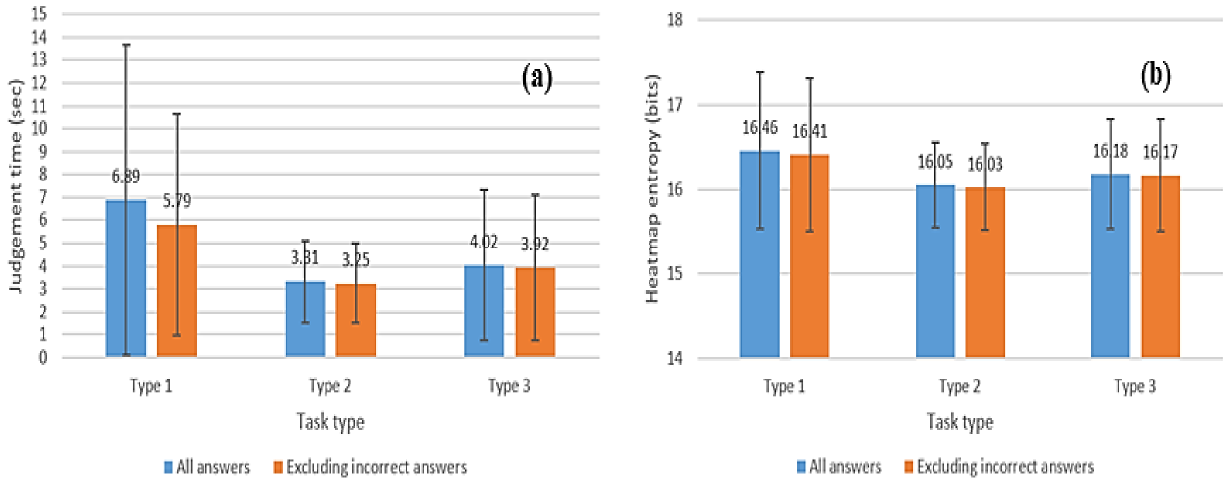


Fig. 2 (a) Mean and standard deviation of judgment time by problem type; (b) Mean and standard deviation of heat map entropy by problem type.

time and heat map entropy including incorrect answers (i.e., cases that failed to judge the system state) was slightly higher than the excluding it. Therefore, it can be predicted that judgment time and heat map entropy may vary depending on the success or failure of the judgment. To verify the characteristics, the judgment time and heat map entropy were analyzed according to the success or failure of the judgment. Looking at the mean judgment time in Fig. 3(a), it can be observed that the judgment time of incorrect answers is much larger than that of correct answers. The difference was statistically significant at a significance level of 0.05 (F=45.426, p=0.000). This means that the correct answer was presented through quick decision-making, but much time was wasted in judgment in the case of incorrect answers. In addition, the deviation in the judgment time of the incorrect answer to judge the system state is much longer than that of the correct answer.

Looking at the mean of the heat map entropy in Fig. 3, it can be seen that the heat map entropy of incorrect answers is higher than that of correct answers. The difference was statistically significant at a significance level of 0.05 (F=7.610, p=0.006).

This means that the gaze distribution of incorrect answers appears to be more dispersed than that of the correct answer. In other words, only a few components were intensively gazed upon in the case of the correct answer, but this means that the gaze was dispersed to several elements in the case of an incorrect answer. This can be understood by looking at Fig. 4, which shows the heat map of correct and incorrect judgment. Fig. 2(a) shows a heat map of a subject who made a correct judgment and Fig. 2(b) shows a heat map of a subject who made an incorrect judgment. In Fig. 2(a), the gazes are concentrated on a few components, whereas in Fig. 2(b), they are dispersed on many components.

The analysis showed that the judgment time and heat map entropy were larger in the incorrect judgment, and the difference also showed the same statistical significance. This result means a close relationship exists between the judgment time and the heat map entropy, as in the analysis by problem type.

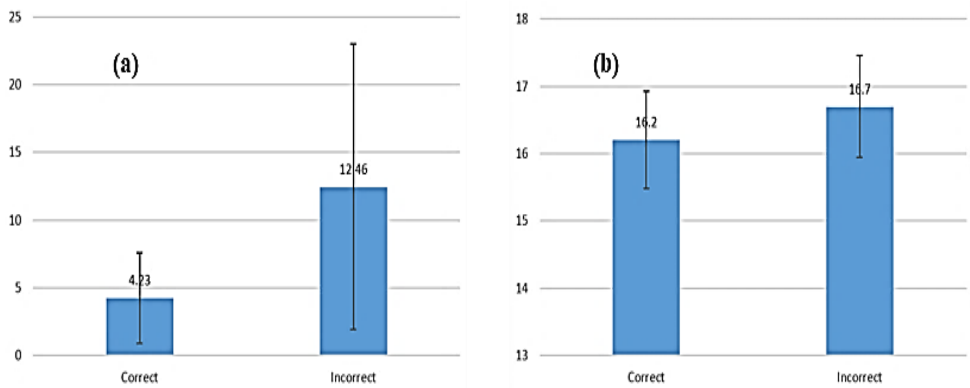
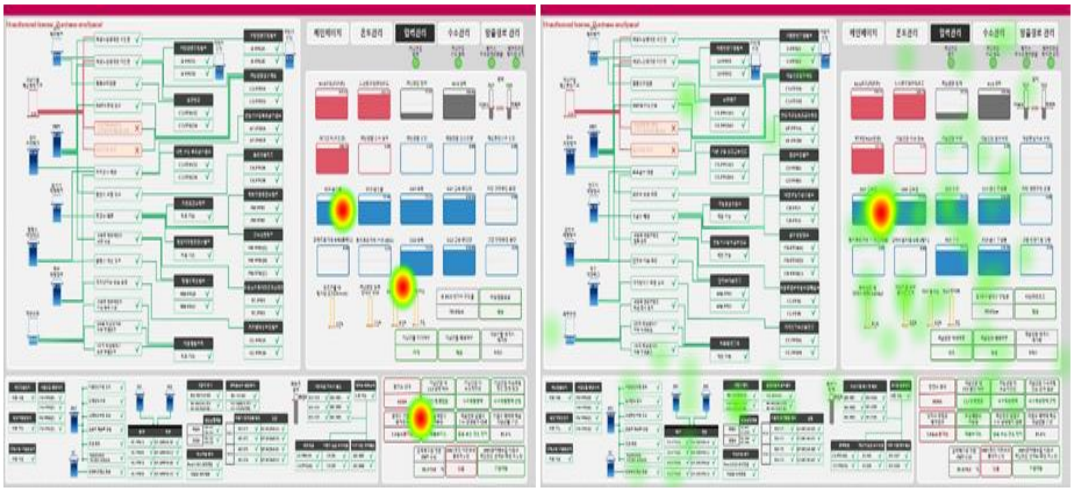


Fig. 3 (a) Mean and standard deviation of judgment time according to the success or failure of judgment; (b) Mean and standard deviation of heat map entropy according to the success or failure of judgment.



(a) (b)

Fig. 4 Example of (a) heat map of correct judgment; (b) incorrect judgment.

3.3 Correlation between heat map entropy and judgment time

From the analysis of judgment time and heat map entropy according to the problem type and the success or failure of judgment, it can be seen that there is a close relationship between heat map entropy and judgment time in the system state judgment task using a visual interface screen. Therefore, correlation analysis was performed to verify the precise relationship between judgment time and heat map entropy. Table 1 presents the results. Heat map entropy and judgment time showed a high correlation (ρ=0.595). In other words, the heat map entropy increases as the judgment time increases, which means that the gaze is distributed to various components. The relationship can be confirmed in Fig. 5, which shows the scatter plot and regression equation between judgment time and heat map entropy. The graph shows that when the heat map entropy increases, the judgment time also tends to increase. The judgment time can be predicted from the heat map entropy using Equation (4).

$$Judgment\ time = -64.73 + 4.28 \times heat\ map\ entropy \quad (4)$$

Table 1. Correlation analysis between heat map entropy and judgment time.

		Heat map entropy	Judgment time
Heat map entropy	Pearson Correlation	1	.595**
	Sig. (2-tailed)		.000
	N	240	240
Judgment time	Pearson Correlation	.595**	1
	Sig. (2-tailed)	.000	
	N	240	240

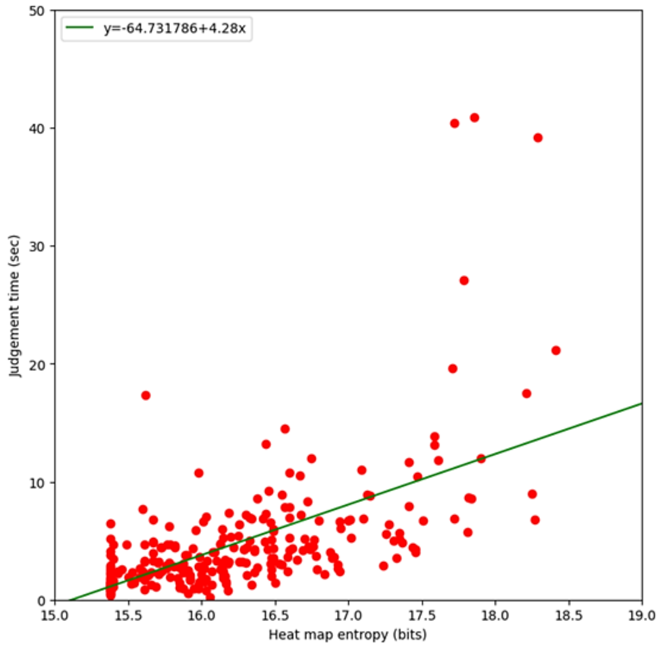


Fig. 5 Scatter plot and regression equation between judgment time and heat map entropy.

3.4 Discussion

This study was performed to verify the relationship between human performance and heat map entropy in the task of judging the system state using a visual interface screen. From the analysis of the heat map entropy and judgment time according to the problem type, the order of magnitude of the heat map was the same as the judgment time, and the differences also showed the same statistical significance. From the analysis of heat map entropy and judgment according to the success or failure of judgment, the judgment time and heat map entropy were larger for the incorrect judgment, and the difference also showed the same statistical significance. From the correlation analysis between the judgment time and heat map entropy, the judgment time showed a high correlation with the heat map entropy. This study verified that human performance and heat map entropy in tasks of judging a system state from a visual interface screen are closely related.

The longer the judgment time for the system state on the visual interface screen, the greater the heat map entropy. This means that the gaze is distributed among several elements in a case where the judgment time is long.

These results are consistent with those of previous studies. Lee *et al.* found that gaze plot entropy was lower when task performance was higher than when task performance was low.[16] Likewise, they argued that the higher the performance of situation awareness, the lower the gaze entropy.[17] Merwe *et al.* reported that gaze entropy was high when an error occurred and situation awareness was low.[18] Bhavsar *et al.* confirmed that gaze entropy is low when a task is successful.[19]

6. Conclusions

In conclusion, long or unsuccessful judgments on the visual interface screen are due to difficulties in finding the necessary information from the screen, which increases the heat map entropy because it causes unnecessary eye movement. This implies that the screen was improperly designed. Therefore, heat map entropy can be used to predict the judgment time on the visual interface screen, which means that it can be used as an indicator to evaluate the suitability of the visual interface design. The heat map entropy increases when the user gazes at more components to find the necessary information and when the gaze intensity for each component is similar. Therefore, increased heat map entropy indicates that the visual interface screen is inadequately designed.

A limitation of this study is that it was conducted on the visual interface screen of the EID-based accident response support system, and university students were used as subjects. Nevertheless, this study can be meaningful in providing evidence that heat map entropy can be effectively used to evaluate the suitability of visual interface screen design. In the future, it will be necessary to generalize the results of this study to other visual interface screens and subjects.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Applicable.

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