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ORIGINAL ARTICLE

Influence of information overload on operator's user experience of human–machine interface in LED manufacturing systems

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Abstract This paper reports on an experimental study on human–machine interface in LED manufacturing systems to measure the influence of information overload on user experience. The results are based on cognitive ergonomics. The experiment used eye-tracking methods and a questionnaire to gather data. The independent variables were interface complexity and user background. Interface complexity had three levels: high interface complexity, moderate interface complexity and low interface complexity. User background had two levels: the novice group and the expert group. The dependent variables included time to first fixation, fixations before and subjective feelings. A total of 38 operators participated in the experiment, and the results showed that (1) interface complexity caused a significant difference in time to first fixation ($P < 0.05$) and fixations before ($P < 0.05$). Furthermore, the results revealed significant differences between high complexity interfaces compared to low complexity interfaces ($P < 0.05$). However, no significant differences were observed between moderate and low complexity interfaces or between moderate and high complexity interfaces ($P > 0.05$); (2) user background significantly affected the user experience; (3) within the same complexity level, expert operators' cognitive workload was significantly lower than that of novice operators; and (4) there was no significant relationship between the interface complexity and the user's background. The study concludes that because interface complexity has a significant effect on the time taken to locate the target button on the screen, interface design should be as simple as possible, while still providing the necessary level of functionality.

Keywords Information overload · User experience · LED manufacturing systems · Human–machine interface · Eye tracking

1 Introduction

With the rapid development of digital manufacturing, human–machine interface (HMI) in LED manufacturing systems presents an increasing trend of information overload and redundancy. HMI refers to the interface that allows a user to understand and operate a machine in a digital manufacturing scenario. Since digital manufacturing requires complex information input and output processes, designing the interface must consider such diverse fields of knowledge as cognitive psychology, industrial design, information processing theory, and human factors (Oborski 2004).

Earlier development considered HMI mainly as a "function first" process in which the user adapts to the equipment. Such a process often required obscure, non-nutritive understanding of the human–machine system and resulted in ineffective operation of those systems (Oborski 2003). Insufficient consideration of the human factors in the man–machine system caused low operating efficiency and an increase in the error rate. For example, the Three Mile Island nuclear accident in 1979 was due at least partly to the lack of consideration given to interface ergonomics factors in designing the control room. According to the research, in 1986, the Chernobyl nuclear power plant explosion was also partly due to HMI design flaws in the control room. In both incidences, failure to adequately

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account for HMI in design had a tremendous impact on the normal production of the manufacturing companies.

Modern digital HMI has numerous characteristics, such as information complexity (Yockey 2002), structure complexity (Zhang 2012), task complexity (Liu and Li 2012) and complex environment (Maldonado et al. 2013). Operators must control a variety of devices in a specific manufacturing environment. People working in this environment not only rely on their eyes to observe the environment, but also depend on machine monitoring systems to help complete precise control actions. Mental workload refers to the psychological pressure on a user during a particular operation or completion of a complex task. Too much information on display can distract the user and increase his or her mental workload. Therefore, operational requirements should maintain a balanced amount of information (Stickel et al. 2010).

Generally, HMI includes two aspects: the "hard man–machine interface," which contains the control panel, control buttons, joysticks, signal lights and so on, and the "soft man–machine interface," which contains a variety of user control options (buttons, labels and so on) accessed via the screen display or touch screen. In this paper, we focus on the "soft man–machine interface."

Previous user experience studies mostly focus on information graphics (Goldberg and Helfman 2011), e-learning (Ramakrisnan et al. 2012), online interface (Spiekermann and Korunovska 2014) and web interface design (Chevalier et al. 2014; Lu et al. 2011; Roth et al. 2013; Tuch et al. 2009, 2011, 2012). Savioja et al. (2014) has reported that user experience research is important in complex manufacturing systems. However, little research has been done on user experience of HMI in manufacturing scenarios, especially in LED manufacturing systems. Furthermore, related research has demonstrated that HMIs in LED manufacturing systems have significant differences compared to those in traditional manufacturing systems; these differences include the system features, the mode of cognitive mechanisms and so on. Accordingly, there must be a sense of urgency in conducting research that focuses on HMI in LED manufacturing.

In this paper, we conducted a visual search experiment in human interface design. The independent variables in this study were interface complexity and user background. The dependent variables are the time to first fixation, the fixations before and subjective feelings. Using an eye-tracking method, we are able to analyze the physiological behavior of participants during task completion and thus better identify the difficulties they have when finding the target button of the HMI in the LED manufacturing systems. The theoretical framework for this study is outlined in Fig. 1.

2 Related research

2.1 User experience evaluation

User experience design (UED) refers to the observation and evaluation of a user's multidimensional experience of a user interface on the basis of such things as behavioral responses as well as psychological and emotional experiences (Bargas-Avila and Hornbæk 2011). UED is the core of user-centered design, which refers to the user as the center of design decisions during the development process. Norman (2002, 2004) divided the design experience into three levels: visceral, behavioral and reflective. On the product experience side, Desmet (Desmet and Hekkert 2007) proposed another three levels of experience: esthetic experience, experience of meaning, and emotional experience. User experience and usability have a close relationship in modern design processes. The International Standard ISO 9241-11 defines usability as, "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use" (Iso 1998). Additionally, Shackel (1991) defined usability as "in accordance with the functional characteristics of the human, the system easily and effectively used by specific user groups." Nielsen (Nielsen 1994) suggested that the product or system should meet a social and practical acceptability.

Furthermore, Hornbæk (2006) identified the following measures for user experience evaluation: effectiveness (through error rates, completeness), efficiency (through task completion time, mental effort) and satisfaction (through post-use questionnaires). Vermeeren et al. (2010) reviewed the current state of the available user experience evaluation techniques, including questionnaire, self-reporting, thinking aloud and psycho-physiological measures. Later, Roto (Roto et al. 2011) collected a comprehensive set of user experience evaluation methods (UXEM) from academia and industry, which included such methods as evaluating emotions (observation; pupil, heart and skin reaction; questionnaires; etc.). In addition, Park et al. (2013) proposed quantification models that integrate major elements of user experience (UX) into a single index. A total of 22 hierarchical dimensions were evaluated, such as overall UX, its elements (i.e. usability, affect and user value) and so on. Moreover, Shin et al. (2013) completed research on the user experience research model in three-dimensional virtual environments. Users' responses to questions about cognitive perceptions and continuous use were collected and analyzed, and the findings confirmed the significant role played by users' cognitive perceptions in their overall experience. Meanwhile, most research using the questionnaire evaluation method

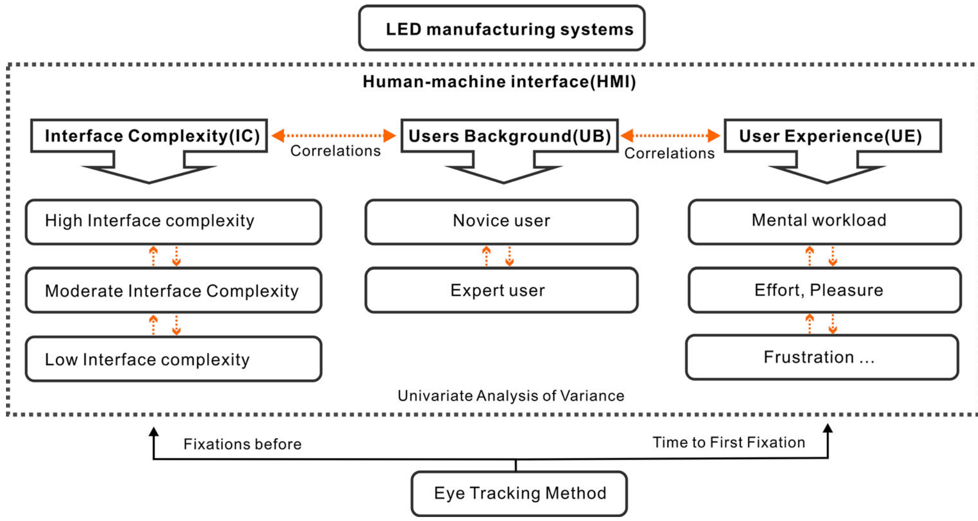


Fig. 1 The theoretical framework of this study

requires user to rate their experiences using Likert scales (usually a 5- or 7-point scale). There are several questionnaires available that evaluate users' subjective feelings, including NASA-TLX, Questionnaire for User Interface Satisfaction (QUIS) and Software Usability Measurement Inventory (SUMI) (Seffah et al. 2006).

Based on the user experience evaluation research above, this paper measured the user experience by collecting user's psycho-physiological data (eye-tracking data) combined with questionnaire evaluation methods based on a Likert scale. In this study, we used a combination of NASA-TLX and QUIS to measure operators' subjective feelings and workload throughout the experiment. The rationale for choosing these questionnaires is in Sect. 3.1 of this paper.

2.2 Eye-tracking metrics

Eye movement research is considered to be the most effective method for measuring visual information processing. Eye tracking is important for evaluating environments within the context of humans working conditions. Studying the steps taken to perform a specific task requires analysis of the individual procedures performed. For this analysis, eye movements present measures that can provide insights into the visual, cognitive and attentional aspects of human performance (Duchowski 2002). Pernice and Nielsen (2009) recommends at least 30 valid data subjects to get a stable heat map.

Previous studies evaluated users' eye-tracking behavior based on the time to first fixation, fixations before and many other metrics. For example, Goldberg and Kotval (1999) conducted research on using eye movement to evaluate the effect of different interface designs. Several measures based upon eye movement locations and scan paths were evaluated to assess their validity for assessment of interface quality. Augustyniak and Tadeusiewicz (2006) presented a new approach to the interpreting data based on eye-tracking features captured from a human expert during visual inspection. The visual experiment required 17 experts and 21 students to perform a visual task and revealed distinctive parameters for using eye tracking to estimate interpretation skills. Ito and Speer (2008) evaluated eye metric (mean fixation proportions) during visual searches. Burch et al. (2011), on the other hand, used eye-tracking methods of heat maps, gaze plots, and areas of interest (AOI) to evaluate participants' reactions to different tree diagrams. Liu et al. (2011) utilized eye-tracking technology to determine the impact of redundant onscreen text information on cognitive processes with respect to multimedia information. The number and duration of fixations as well as average fixation durations were analyzed to compare participants' information processing strategies while viewing web pages. The participants' self-reported mental-effort ratings were collected as indicators of the level of cognitive load. Veneri et al. (2012) evaluated human visual search performance using an eye-tracking method. The paper evaluated the visual selection process during the execution of a high cognitively demanding task in order to discover how selection (fixations) guided subsequent exploration (saccades). The results were calculated by the distance of saccades from fixed points and the distribution of fixations. Chen and Pu (2014) used measures of fixation frequency, fixation duration and AOI. They reported the results of two studies that compared two recommender interfaces. The empirical findings suggested that the change in recommender interface design not only altered users' attention distribution, but also influenced their subjective attitudes toward the system. Furthermore, Zulch and Stowasser (2003) evaluated metrics of the number of fixations and the length of time before first fixations which could be recorded through observation of different user strategies in searching data. The aim of the paper was to detect relationships between different types of data representation.

Based on the eye-tracking research reviewed above, we chose to use the eye-tracking metrics AOI, time to first fixation, and fixations before to evaluate operators' visual searching behavior. The rationale for choosing these measures is included in Sect. 3.1.3.

3 Methods

3.1 Definitions

In order to confirm the following hypotheses, we designed a multiple-variable experiment study. The two independent variables in this study are interface complexity and user background. The dependent variables are time to first fixation, fixations before and subjective feelings. In this paper, we measure user experience using eye-tracking data (objective metric; time to first fixation and fixations before) combined with a subjective feelings questionnaire (subjective metric; responses based on a 7-point Likert scale), see Fig. 2.

3.1.1 Interface complexity

Interface complexity metrics were determined by the number of elements in the interface, the density of interface elements and their arrangement in relationship to other interface elements. Interfaces were ranked as having high, moderate, and low complexity. In this study, high interface complexity is designed by having the number of 90 elements, a high density of interface elements and a complex relationship between interface elements. In contrast, low interface complexity presents the number of 37 elements, a low density of interface elements and a simple relationship between interface elements. Moderate interface complexity is designed by having the number of 59 elements, a medium density of interface elements and a moderate relationship between interface elements (see Table 1).

3.1.2 User background

User background had two levels: the novice group and the expert group. User background was defined by experience relating to the experiment task and years of practice in the company. The novice group included participants who had no experience with the relevant task and less than 1 year of practice in the company, while the expert group participants with rich experience with the relevant task and more than 3 years of practice in the company (see Table 2).

3.1.3 Eye-tracking metrics

In this research, we wanted to find out how long it took participants to notice a specific visual element (such as Clear Bin button) in the interface. While we may know how long the operator spends on the interface, it is more helpful to establish (1) that a specific element is noticed within a reasonable time and (2) how long it takes the operator to notice that particular element during his or her work. To understand how interface complexity influences the completion of such a visual searching task, we choose time to first fixation and fixations before as the main eye-tracking research metrics.

Time to first fixation (measured in seconds) measures how long it takes before a participant fixates on an AOI for the first time. The time measurement starts when the media is first displayed and stops when the participant fixates on the AOI. If, at the end of the recording, the participant has not fixated on the AOI, the time to first fixation value will not be computed, and that recording will not be included in the descriptive statistics calculations.

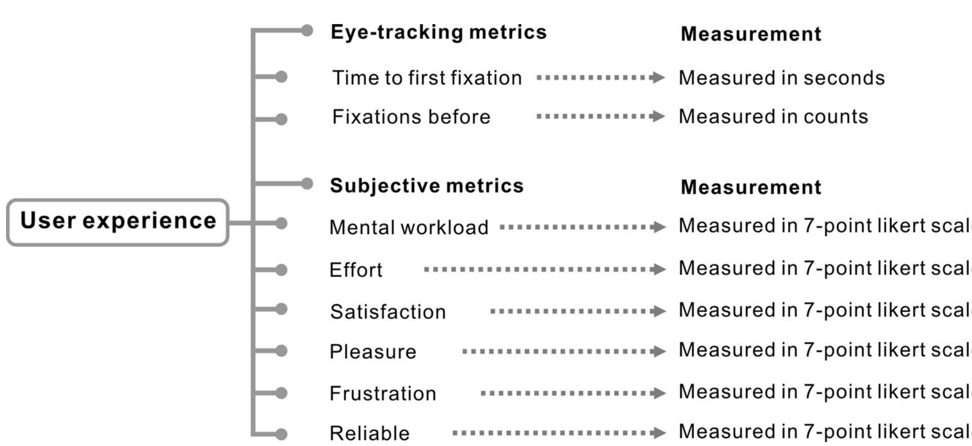


Fig. 2 The measurement metrics system of user experience

Table 1 The definition of the three levels of interface complexity

Name	Stimuli A	Stimuli B	Stimuli C
Number of elements	37	59	90
Density of elements	Low	Medium	High
Relationship between elements	Simple	Moderate	Complex
Interface complexity	Low interface complexity	Medium interface complexity	High interface complexity

Table 2 The definition of user background

Name	The novice group	The expert group
Experience about the relevant task	No experience about the relevant task	Rich experience about the relevant task
Years of practice in the company	Less than 1 year	More than 3 years

Fixations before (measured in counts) measures the number of times the participant fixates on the media before fixating on the AOI for the first time. The fixation count starts when the media is first displayed and it stops when the participant fixates on the AOI. As with time to first fixation, if the participant has not fixated on the AOI at the end of the recording, the fixation before value will not be computed, and that recording will not be included in the descriptive statistics calculations.

AOI is a very useful tool for quantifying gaze data. The researcher can define AOI on the interface and then use those AOI to calculate different eye movement metrics for statistical analysis. The gaze plot is another useful tool when visualizing the operator's scan paths and search behavior. Looking at the fixations in a gaze plot establishes where the operators fixated during the task. Heat map visualizations are mainly used for the agglomerated analysis of operators' visual exploration patterns. Furthermore, heat maps provide graphical representations of data where the individual values contained in a matrix are represented as colors. We base our analysis of participants' exploration behavior on the AOI as derived from the amount and density of the heat map representations.

3.1.4 Subjective feelings measure

The questionnaire in our experiment was based mainly on NASA-TLX (Rubio et al. 2004), which allowed us to perform subjective workload assessments on operators working with various human–machine systems. We did not consider factors such as the physical demand in our measures, because operating LED HMIs place few physical demands on the user. Temporal demands and performance could be measured by eye-tracking metrics, so we also did not consider those two factors. QUIS was designed to assess users' subjective satisfaction of the human–computer interface. We added factors related to user experience such as user satisfaction, pleasure (from overall user reactions) and reliability (from system capabilities) extracted from the QUIS questionnaire. We choose the QUIS from among the different questionnaire because is especially suitable for evaluating software interfaces in visual display terminals. Thus, QUIS operates between the designer domain of concrete product attributes and the user domain of subjective experience.

Table 3 The experiment questionnaire

Number	Question
Q1	I think the user satisfaction was perfect in the task
Q2	I think the mental workload was low in the task
Q3	I think the effort was low in the task
Q4	I think the pleasure was high in the task
Q5	I think the frustration was low in the task
Q6	I think the reliable was high in the task

The subjective feelings questionnaires for the experiment were printed on A4 paper, using single-sided printing. The evaluation was based on a 7-point Likert scale, where 7 indicated strong agreement, 1 indicated strong disagreement, and 4 was neutral (see Table 3).

3.2 Hypotheses

The hypotheses of this study are as follows:

H1 Interface complexity significantly affects the user experience.

H2 User background significantly affects the user experience.

H3 Interface complexity and user background have significant interaction effects.

3.3 Participants

A total of 38 operators at Guangdong Zhicheng-Huake Optoelectronic Equipment Co. Ltd. were randomly selected to participate in this experiment. There were 21 male and 17 female operators, ages 18–32 (mean age = 23.64, SD = 2.13). Male subjects accounted for 55.3 % of the study, and female subjects accounted for the remaining 44.7 %. The novice group and the expert group each consisted of 19 people. All participants had normal or corrected-to-normal color vision, 10 participants wore glasses and 3 of them wore contact lenses. None of the participants had prior eye surgeries or eye problems such as "droopy" eyelids.

3.4 Stimuli and task

As the experimental stimuli in this experiment, we designed three prototype of the HMI in LED high-speed automatic sorting system. Three experimental stimuli (screenshots of prototype, JPG format and 1920 × 1080 pixels) were chosen to present information at three levels of complexity: low interface complexity, moderate interface complexity, and high interface complexity, as shown in the top row. There was only one fixed AOI in each of the interface screen, as shown in the second row. In addition, the location of the AOI was slightly adjusted in each complexity of the interface to eliminate learning effects, as shown in the third row (see Fig. 3).

The Clear Bin button operates one of the most important steps in LED high-speed automatic sorting system. Therefore, we chose the Clear Bin button as the visual searching target button. We designed the eye-tracking task of finding the clear bin button in the interface. This primary task was chosen because the participants had to apply the visual searching task to find the different eye movement behavior based on different interface complexity. In each task, the target button (Clear Bin button) is defined as the AOI. Time to first fixation in the experiment is defined as the time between the interface showing up and the participant visually identifying the AOI.

We designed a within-subjects study design with 38 participants. All participants were involved in all three levels of interface complexity task. We counterbalanced the three experiment stimuli (low interface complexity, moderate interface complexity, high interface complexity) using a random method to compensate for learning effects. Participant was asked to complete three visual search tasks in random order. For example, participant 1 conducts the task 1 (low complexity), task 2 (moderate complexity) and task 3 (high complexity); Participant 2 conducts the task 1 (high complexity), task 2 (moderate complexity) and task 3 (low complexity), Participant 3 conducts the task 1 (moderate complexity), task 2 (low complexity) and task 3 (high complexity), etc. The three task composition six different permutations. Each task was conducted one time for each participant. During each task, there are 5 s of break time (gray screen). The design of eye-tracking experiment was showed in below (see Fig. 4).

3.5 Equipment and environment

Eye movements were sampled at 300 Hz using the Tobii X300 eye tracker (Sweden, 23-inch screen size, 16: 9 screen resolution, 1920 × 1080 pixels). The initial positions of fixation points for trials using the Tobii X300 are at the center point of the interface screen. The Tobii X300 eye tracker performs robust eye tracking and compensates for large head movements (freedom of head movement at 37 × 17 cm; maximum head movement speed at 50 cm/s), thus extending the possibilities for researching eye-tracking behavior. Tolerance for head movements allows subjects to move naturally in front of the stimuli and capture natural human behavior without the need for a chin-rest. The Tobii X300 system support is also able to track subjects who use glasses, contact lenses or mascara. Data gather by the tracker can be analyzed using Tobii Studio version 3.2.1, which provides a framework for quantitative analysis of eye-tracking data.

The test environment was a quiet LED manufacturing laboratory without noise and interference. Participants were instructed to switch off their mobile phones to reduce possible distractions during the experiment. The room was artificially illuminated, and only a minimum of objects was contained inside. Participants sat in front of the Tobii X300 monitor in chairs set at a distance of about 60 cm from the monitor. Desk and monitor position and height were fixed. The chair was adjustment to fit participant's natural angles of elbow and knee.

3.6 Procedure

Before the experiment began, participants were asked to read an introduction of the experiment requirements and then sign the "Experimental Informed Agreement". After signing the "Experimental Informed Agreement," allowed the participants to listen to soft, relaxing music for 30 s. Next, they read a short manual about the experiment stimuli to insure they were able to understand and solve the given task.

When the participant was ready, we started the eye-tracking experiment. The participants were asked to find the Clear Bin button in each task. We recorded the time and the gaze plot it took them to find the AOI. Until the participants confirmed they had found the "Clear Bin" button (time measurement automatically stops when the

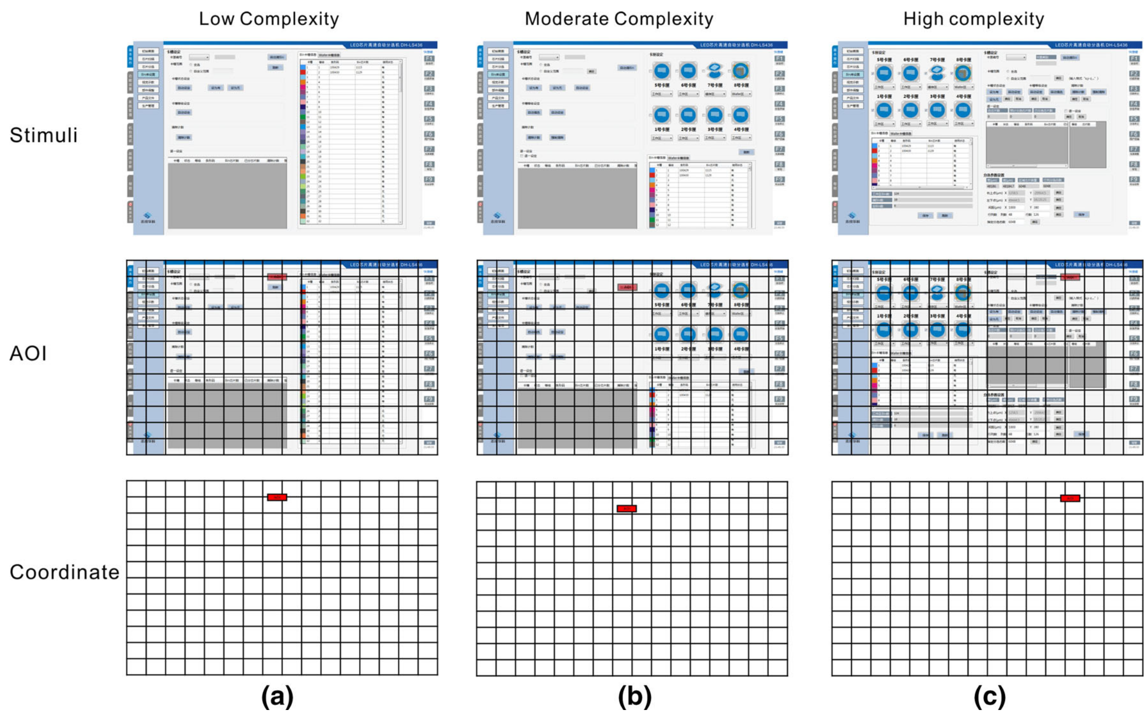
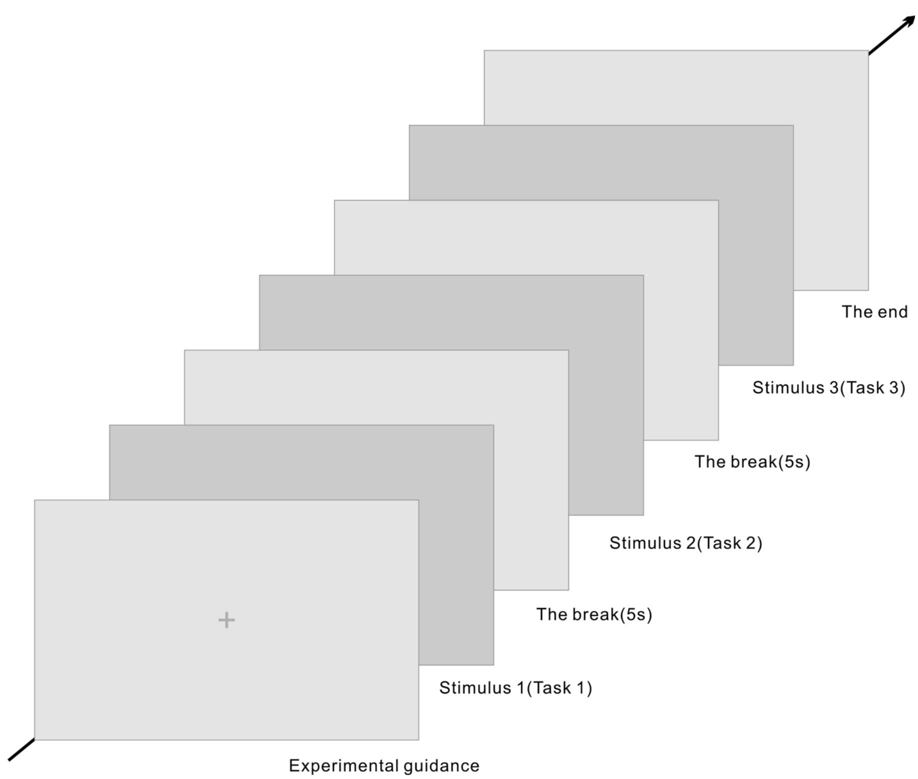


Fig. 3 The experimental stimuli and the AOI in each of the interface screen. *Left columns* **a** 37 interface elements, low density of elements and simple relationship between elements (low interface complexity). *Middle columns* **b** 59 interface elements, medium density of elements and moderate relationship between elements (moderate interface complexity). *Right columns* **c** 90 interface elements, high density of elements and complex relationship between elements (high interface complexity)

Fig. 4 The design of eye-tracking experiment



participant fixates on the AOI), and then they needed to tap "Space Bar" by their forefinger of the right or left hand to the next task (see Fig. 5). The reason to tap the "Space Bar" of keyboard is that to eliminate the visual influence of the mouse cursor on the interface screen. After taping the "Space Bar" of keyboard, participants entered the next task. The eye-tracking duration of each task was 1–6 s based on the task. After all the three tasks were finished, participants were immediately asked to complete the subjective feelings questionnaire. The questionnaire answers were manually recorded by the operator. Finally, 38 participants completed all the 114 tasks (38 participants $\times$ 3 tasks).

4 Results and discussion

This paper reports on an eye-tracking study that investigated the relationship among interface complexity, user background and user experience as suggested in the hypotheses. The study focused on evaluating the eye movements and subjective feelings of participants from difference user backgrounds, while they experienced varying levels of interface complexity.

We found that an interface with lower complexity could significantly increase the user's attention as compared to an interface with higher complexity. Our research findings indicate that user background also influenced participants' subjective feelings. The novice group felt significantly higher levels of effort, frustration and mental workload when compared to the expert group, and experienced less pleasure and reliability. The ANOVA analysis was used to examine the association between interface complexity and user experience. As a result, interface complexity significantly altered user satisfaction ($P < 0.05$), mental workload ($P < 0.05$), effort ($P < 0.05$), pleasure ($P < 0.05$), frustration ($P < 0.05$) and, to a lesser degree, reliability ($P > 0.05$). The reliability factor did not show statistical significance because the sense of trust and security was common in HMI in manufacturing scenario.

4.1 H1: Interface complexity

A one-way ANOVA was used to examine the association between interface complexity, time to first fixation and fixations before. Time to first fixation and fixations before were the dependent variables; interface complexity was an independent variable. The results showed that the interface complexity caused a significant difference in the time to first fixation ($P < 0.05$) and fixations before ($P < 0.05$). Furthermore, post hoc tests were performed to test the P value. The Tukey HSD test for each interface complexity level showed significant differences between high interface complexity and low interface complexity ($P < 0.05$), but no significant differences between moderate and low interface complexity ($P > 0.05$) or between moderate and high interface complexity ($P > 0.05$) (see Table 4).

The gaze plot visualization showed the sequence and position of fixations on the interface. The size of the dots indicates the fixation duration, and the numbers in the dots represent the order of the fixations. First, we compared the gaze plot visualization data from each of the three interface complexity levels. The data showed that as the interface complexity increased, the gaze plot gradually become more complicated and disorderly. The results indicate that as interface complexity increases, there is an increase in the user's cognitive workload and the visual search tracks become longer and more dispersed over the interface area.

Fig. 5 Participant in the experiment and the environment

Table 4 Multiple comparisons

Dependent variable	Complexity (I)	Complexity (J)	Mean difference (I − J)	SE	Sig.
Time to first fixation	Low complexity	Moderate complexity	−1.755000	0.995184	0.201
		High complexity	−3.235000[a]	0.995184	0.008
	moderate complexity	Low complexity	1.755000	0.995184	0.201
		High complexity	−1.480000	0.995184	0.313
	High complexity	Low complexity	3.235000[a]	0.995184	0.008
		Moderate complexity	1.480000	0.995184	0.313
Fixations before	Low complexity	Moderate complexity	−7.410000	3.957893	0.166
		High complexity	−12.923000[a]	3.957893	0.008
	Moderate complexity	Low complexity	7.410000	3.957893	0.166
		High complexity	−5.513000	3.957893	0.359
	High complexity	Low complexity	12.923000[a]	3.957893	0.008
		Moderate complexity	5.513000	3.957893	0.359

Tukey HSD

[a] The mean difference is significant at the 0.05 level

Since the user's cognitive capacity is limited, increasing the complexity of the interface decreases the user's effective visual focus.

The heat map used different colors to show the number of fixations participants made in certain areas of the image or how long they fixated within that area. Red indicates the highest number of fixations or the longest time, and green the least fixations or shortest time, with varying levels in between. The heat map observations make clear that the low complexity interface had one hot zone, the moderate complexity interface had two hot zones, and the high complexity interface had five hot zones. In these representations, hot zones with higher density indicate where users focused their gaze with a higher frequency. It appears that the number of hot zones increased as the interface complexity increased. This is most likely caused by the increased difficulty in finding the AOI. The operators were paying more attention on different way-finding areas. These search strategies become significantly more complex during times of information overload (see Fig. 6).

4.2 H2: User background

The frequency of visual gaze manipulation was related to the length of the fixation duration and difficulty of understanding interface information. The gaze plots for the low complexity interface did not show a significant difference between the novice group and the expert group. But as the interface complexity increased, the gaze plots for the high complexity interface indicated a huge difference. For example, the novices' gaze plots in the high complexity interface tracked over nearly the entire interface. This result suggested that when a novice user is faced with a highly complex HMI, information overload result in low efficiency and operational errors. When the expert group faced the high complexity interface, they were better able to analyze the given task and thus reduce the cognitive workload. By effectively ignoring the non-relevant areas of the interface, the expert group saved search time and increased their search efficiency. According to these results, user background does affect the visual search strategies when a user interacts with a complex interface.

Comparing the search performance of the expert users and novice users interacting with interfaces of the same level of complexity also reveals a significant difference ($P < 0.05$). The user background effect can be interpreted directly since there are only two levels of this factor. The time to first fixation of the novice group (1.212, 3.892, 6.126) is significantly longer than that of the expert group (0.758, 1.588, 2.341) at all three complexity levels ($P < 0.05$), which means the search efficiency of the novice group is significantly lower than the expert group. The fixations before of the novice group (5.528, 16.798, 24.872) are also significantly greater than that of the expert group (3.522, 7.072, 10.024) at all three complexity levels ($P < 0.05$). These results indicate that increasing information overload and redundancy reduces users' visual search efficiency. The time to first fixation and fixations before of expert groups were significantly less than the novice groups, which illustrates that the operational performance of the expert group was significantly better than that of the novice group (see Fig. 7).

4.3 H3: Interface complexity and user background

To further validate the research hypotheses, a (3 × 2) factor univariate analysis of the variance was performed on the collected data. For this analysis, the time to first fixation

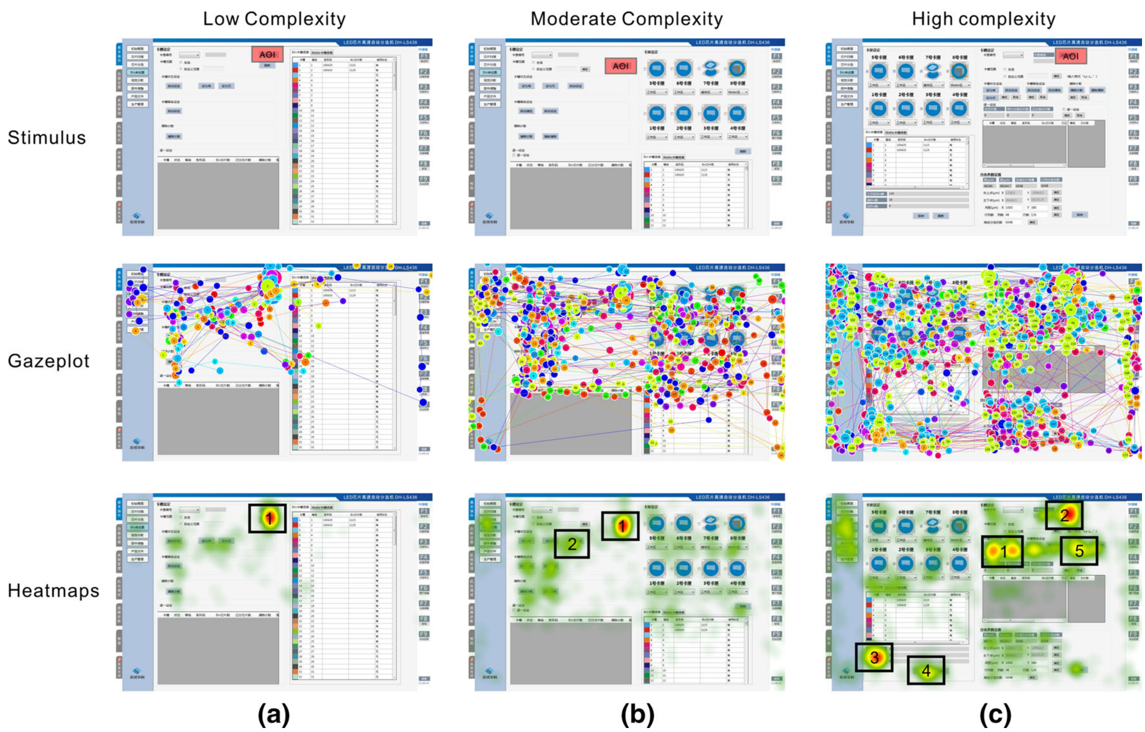


Fig. 6 *Top row*: the experimental stimuli and the AOI. *Second row*: gaze plots for the three interface complexity as illustrated in the *top row* (all the participants). *Third row*: heat maps for area of interest (AOI) determination based on the gaze plot data represented in the *second row* (all the participants)

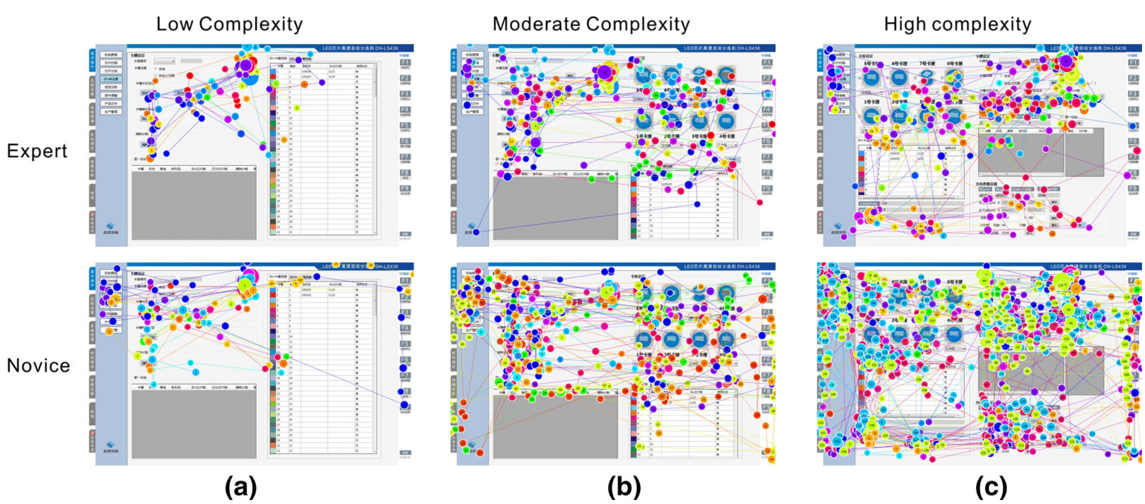


Fig. 7 The gaze plot between the expert group and the novice group (all the participants in each group)

was the dependent variable. Both interface complexity and user background were independent variables. The results suggest that interface complexity produces a significant effect, $F(1,\ 37) = 7.53$, $P < 0.05$. The time to first fixation was significantly higher when engaging with the high complexity interface (M = 4.220, SD = 3.2) when compared with the moderate complexity interface (M = 2.740, SD = 2.1) and the low complexity interface (M = 0.985, SD = 0.3), respectively. Users' background also produces a significant effect on user experience, $F(1,\ 37) = 10.3$, $P < 0.05$. The time to first fixation for expert users (M = 1.553, SD = 0.90) was significantly lower than that of novice users (M = 3.743, SD = 3.14). There is no significant interaction between interface complexity and user background, $F(1,\ 37) = 2.031$, $P > 0.05$. Regardless of interface complexity and users' background, however,

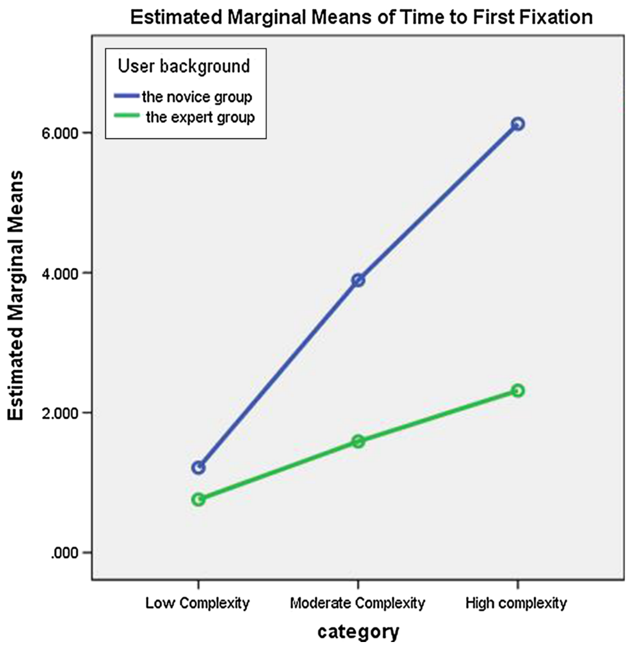


Fig. 8 Significant difference between the expert group and the novice group

after adjusting R Squared $= 0.457$, the results indicate that users have the greatest significant difference effect in their time to first fixation (see Fig. 8).

4.4 Summary

This paper presents a study investigating the effects of interface complexity and user background on visual search tasks by measuring eye movements and subjective feelings. The aim of this research is to assess the impact of both interface complexity and user background on user experience.

Results that can be drawn are as follows: (1) interface complexity caused a significant difference in the time to first fixation ($P < 0.05$) and fixations before ($P < 0.05$). Furthermore, the results revealed significant differences between high complexity and low complexity interfaces ($P < 0.05$), but no significant differences between moderate complexity and low complexity interfaces, which also holds true when comparing moderate complexity and high complexity interfaces ($P > 0.05$); (2) user background significantly affects the user's search strategies. The visual search strategies of novices versus experts show these differences, with the novice group's gaze plots being significantly more complicated compared to those of the expert group; (3) at the same complexity level, expert operator's cognitive workload was significantly lower than the novice operator; and (4) the results showed that there was no significant interaction between interface complexity and user background.

5 Conclusion

In this paper, we reported on an eye-tracking experiment with 38 participants that compared three levels of interface complexity in LED manufacturing systems. We analyzed two levels of user background: novice and expert. A statistical analysis of the data showed that interface complexity significantly affected the user experience. Additionally, we found that the background of the participants significantly affected the time to first fixation as well as the fixations before. These results were consistent with the subjective feelings questionnaire completed by participants after the experiment.

This study investigated visual search strategy relating to HMI in LED manufacturing systems. For users working with a computer display, HMI design plays a role in both safety and preventing fatigue. In this study, eye-tracking technology revealed how operators visually processed different levels of interface complexity. The results indicated that interface complexity significantly affects the operator's visual search strategy. Meanwhile, the user background also significantly affected the visual search strategy. The study found that information overload in interface design increased cognitive workload and therefore decreased user efficiency in the LED manufacturing system environment. Interface complexity has a significant effect on the time taken to locate the target button on the screen, showing that interfaces should be as simple as possible, while still providing the necessary level of functionality. Furthermore, this study provides an approach of using eye-tracking analysis for user interface evaluation in relevant working conditions and industrial applications areas.

However, the limitations of this research should be discussed. (1) The participants: the participants were all from the same company, so they might have a partiality for this study. It would be beneficial to include a wider range of participants in future research. (2) The experimental stimuli: we studied only LED high-speed automatic sorting systems. Future research could use additional types of HMIs used in manufacturing systems. (3) Our study was based only on eye-tracking methods and subjective participants' responses. Future research could include additional biofeedback measures, such as EEG research method. Although this study has its limitation, we hope that it can serve as a basis for future studies.

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