Attention Capture Experimental Paradigm for Cross-Screen Interaction in Nuclear Power Monitoring System

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SUMMARY

This study analyses the mechanism of operators' cross-screen interactive behaviour during the execution of typical monitoring tasks from the perspective of attention capture, in order to enhance the superiority of attention capture for critical task information on interfaces, ultimately improving operators' efficiency in manipulation. The connection between the operator's perceptual cognitive process and cross-screen interactive behaviour is established through the bottom-up and top-down attention capture mechanisms. A cross-screen interaction experimental paradigm is proposed, and experiments are conducted in specific scenarios to verify and refine the potential behavioural mechanisms. The experimental results will help to gain a deeper understanding of the underlying mechanisms of cross-screen behaviour and cognitive processes and reveal the mapping relationship between interface factors and cross-screen interactions.

KEYWORDS

Attention Capture Mechanism, Nuclear Power Monitoring, Cross-Screen Interaction, Experimental paradigm

Introduction

The advancement of intelligent nuclear power technology has intensified human factors challenges in main control rooms (MCRs), particularly regarding multi-screen interactions (Xue, 2015). As shown in Figure 1, the MCR is the "nerve centre" of the nuclear power display and control system and is also a typical multi-screen interactive scene (Zhang et al., 2019). The most common human-computer interaction behaviours is the cross-screen information search activity that occurs on different screens or paper documents (Wu et al., 2018), as shown in Figure 2. Operators must manage information distributed across visual display units (VDUs), large display panels (LDPs), and paper documents at key information centres (KIC), leading to cognitive overload risks including visual fatigue, attention diversion, and decision-making errors. This paper investigates the relationship between operators' cognitive processes and cross-screen interaction behaviours during critical tasks. We propose visualisation methods that optimise interface design through attention screening mechanisms, suppressing non-essential information while enhancing task-relevant data processing. Our approach addresses three key design considerations: 1) Information configuration tailored to specific operational scenarios 2) Feedback mechanisms supporting cross-screen information searches 3) Interactive operations mitigating the cognitive impacts of intelligent system complexity. The research aims to improve information comprehension and reduce human error in next-generation nuclear power control systems.

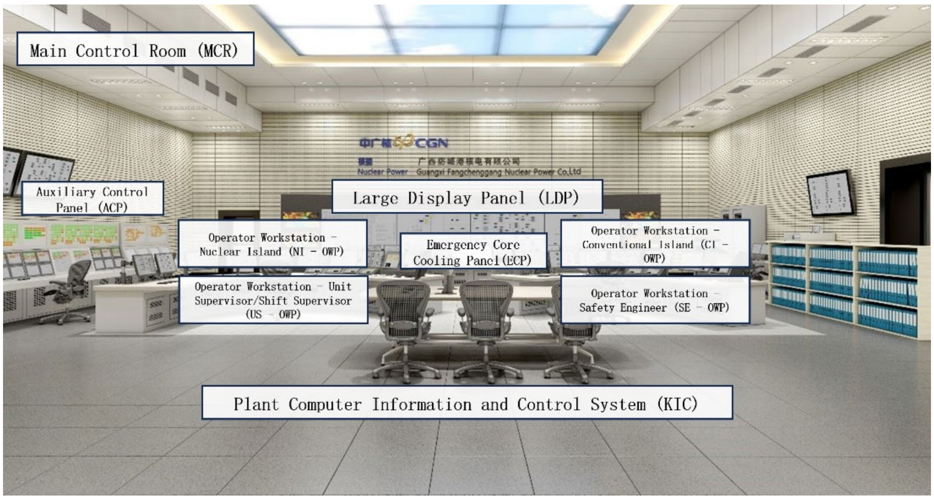

Figure 1. Nuclear power control room layout and working scenes

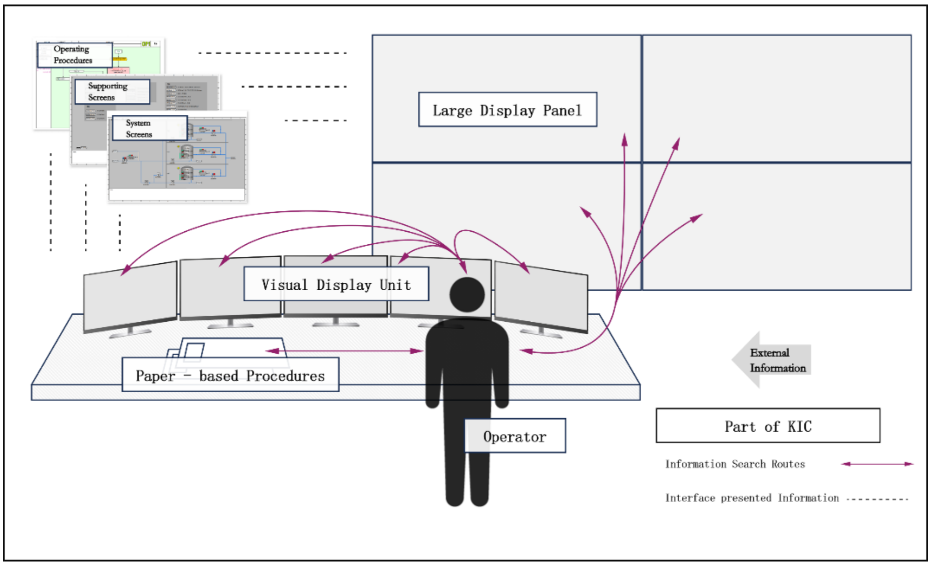

Figure 2. The cross-screen information search activity

Interaction between screens can be divided into same-screen interaction and cross-screen interaction. Cross-screen interaction can be further divided into cross-screen interaction within the same device group and cross-screen interaction across device groups (Nebeling et al., 2013). In the MCR, an operator interacts with multiple VDUs, LDPs and other device groups. Individual cognitive processes guide the attention capture of visual perception. This interaction causes operators to produce individual behaviours based on their own cognitive characteristics. Therefore, the operator's cross-screen interactive behaviours and cognitive process show a close correspondence, involving the interaction between information elements and cross-screen contexts, as shown in Figure 3.

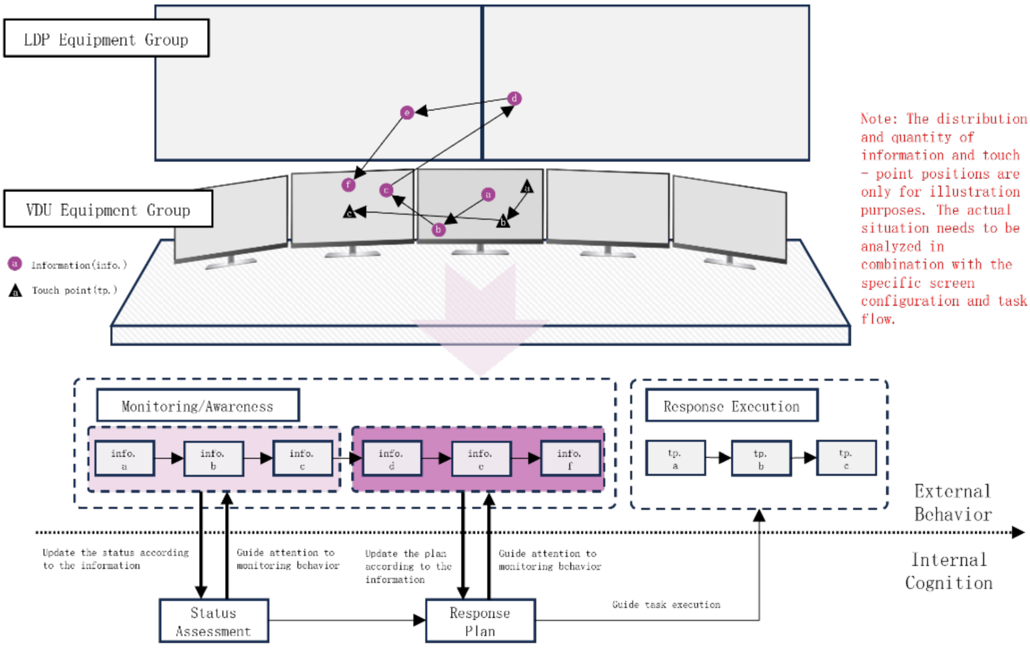

Figure 3. The correspondence between the operator's cross-screen interactive behaviours and cognitive process

The cognitive process of the operator's cross-screen interaction behaviours not only involves the processing and transmission of information, but also deeply reflects the operator's cognitive strategy and behaviours pattern in a specific task environment. In order to deeply understand this behaviours pattern, this process is analysed from the perspective of the attention capture mechanism and a cross-screen interactive behaviours model of the operator based on the attention capture mechanism is constructed, as shown in Figure 4. This model analyses cross-screen interaction behaviours from the perspective of bottom-up and top-down attention capture mechanisms (Posner, 1980), while integrating the interaction between information elements and screen configurations, providing a theoretical basis for subsequent research on cross-screen interaction behaviours mechanisms.

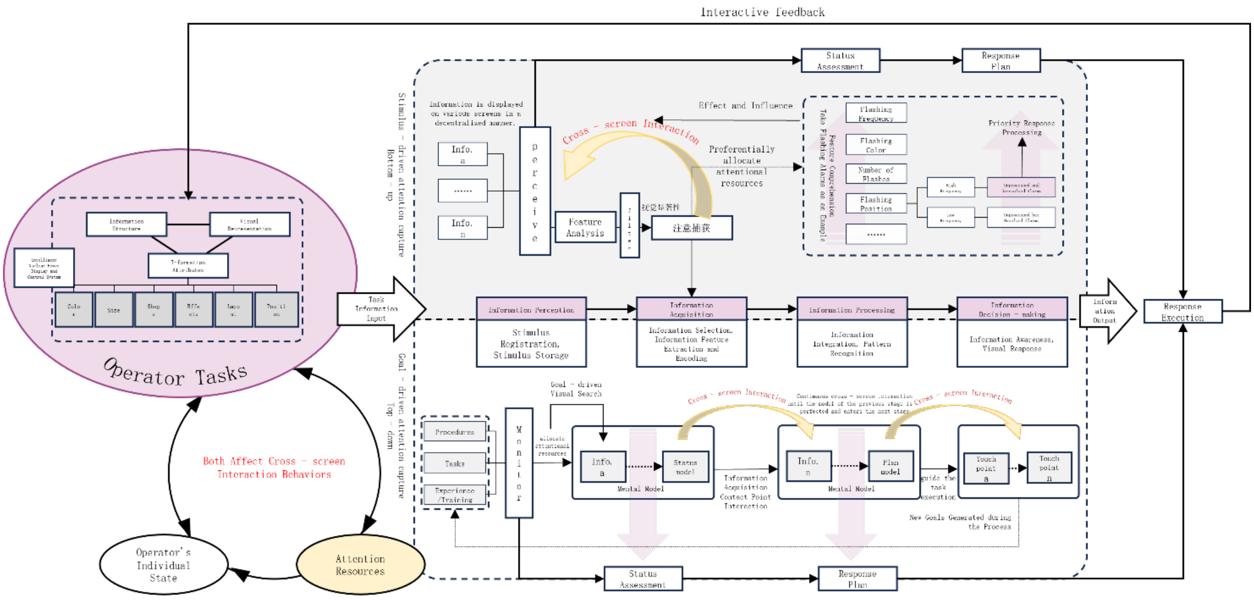

Figure 4. The cross-screen interaction behaviours model based on attention capture mechanism

This chapter details the attention capture mechanism, analysing the operator's cognitive process and cross-screen interaction behaviours. It highlights the importance of this mechanism in cross-screen interactions and proposes a model that integrates the operator's cognition, attention capture, and cross-screen characteristics. The model explains how operators engage in cross-screen contexts influenced by attention capture, providing insight into their behaviours and laying the foundation for experimental paradigms and design.

Methods

Experimental paradigm

Based on the above cross-screen interaction behaviours analysis, a behavioursal experimental paradigm is proposed to study the attention capture effect of operators in cross-screen interaction scenarios. The effectiveness of cross-screen interaction between subjects on different screens is explored from the perspective of attention capture mechanism, as shown in Figure 5.

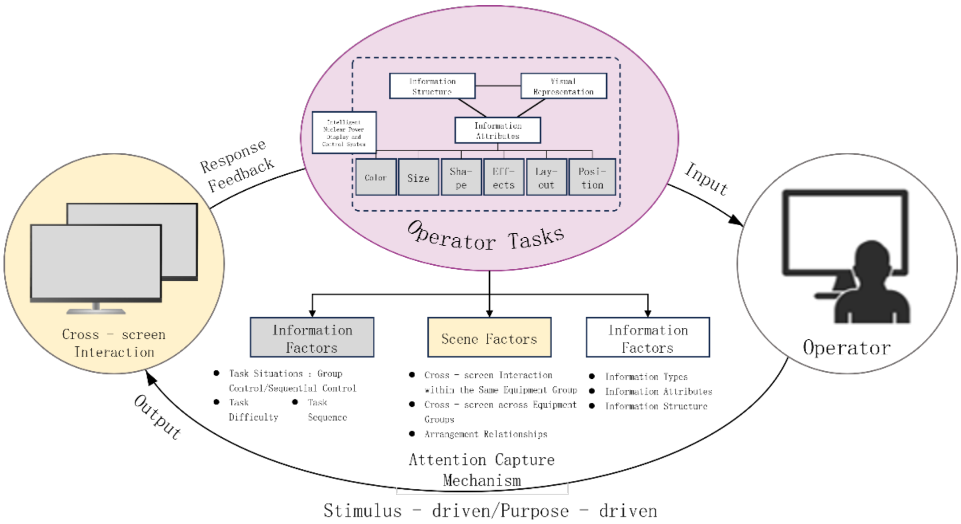

Figure 5. Cross-screen interactive attention capture experimental paradigm under typical tasks of intelligent nuclear power

Experimental design

This experiment uses a cross-screen interaction attention capture paradigm with five VDUs on the operating table. The task involves inserting fault alarm messages during the abnormal diagnosis phase to enhance attention. Psychological, behavioursal, and eye movement data are collected on reaction times, accuracy, and attention-related eye movements (Cheng et al., 2017).

The experimental variables are cross-screen interaction (scene factor) and fault alarm (information factor). Cross-screen interaction includes the number of screens and their orientation, with screen C as the main task starting point. The screen layout and numbering are shown in Figure 6. Fault alarms are defined by three sub-variables: the number of alarms (1-3), alarm level (high: 2 Hz fast flashing, low: 0.5 Hz slow flashing), and alarm location (nine grid positions). The fault alarm form is flashing.

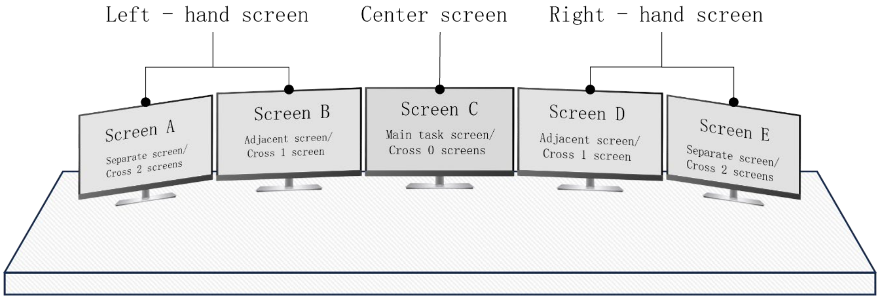

Figure 6. Experimental scene design and screen numbering

Procedures

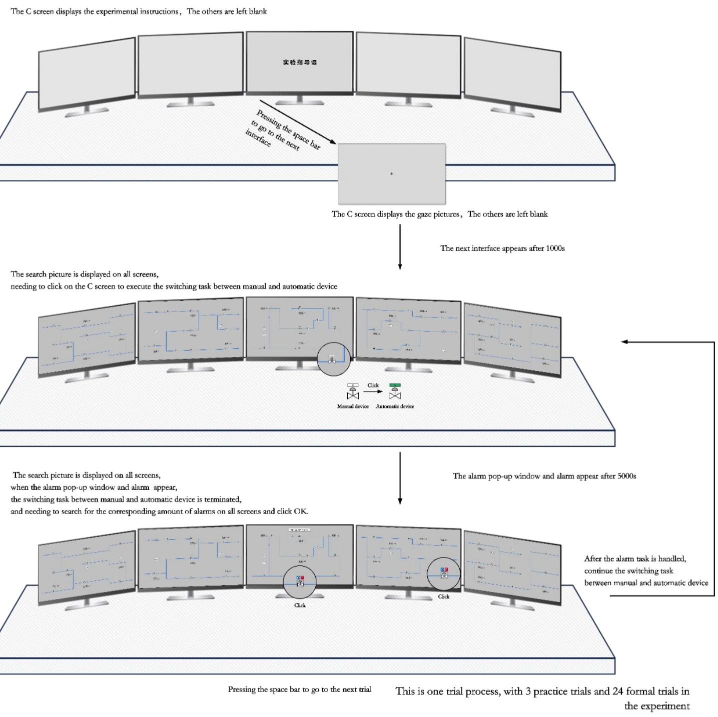

Figure 7. Experimental process diagram

Each subject completes 24 trials with random combinations of independent variables. Before starting, the experimenter provides instructions on a C screen, followed by practice trials. The formal experiment begins with a fixation point ("+") displayed for 1000ms, signaling the start. In the group control task, subjects identify and switch 5 devices from manual to automatic mode by clicking the left mouse button. An alarm pop-up appears during the task, and subjects must pause to locate and confirm the corresponding alarm icons. After handling the alarms, they continue switching the devices until the task is complete. Pressing the space bar starts the next trial. The experimental process is shown in Figure 7. After the experiment, the subjects were required to complete a questionnaire on basic demographic information, including name, gender, age, and years of work experience.

Equipment and Participants

The prototype tool, built in Figma, is tested on an alternating platform using Python's pyautogui and pynput libraries to gather event data. Tobii Glasses, with two eyeglasses, were used, requiring 2-5 minutes for setup before testing. Twelve subjects with experience in nuclear power main control room interface design participated in the experiment, held at the State Key Laboratory of Nuclear

Power Safety Monitoring Technology and Equipment, China Nuclear Power Engineering Co., Ltd. The experimental scene is shown in Figure 8. The subjects, aged 29-44 (average age 35.75), had 4-18 years of work experience (average 7.5 years). All had corrected vision above 1.0 and no color blindness. The experiment used five computers with identical specifications, each displaying 2880x1800px resolution at 64-bit color quality. Subjects sat 55-60cm from the screen.

Figure 8. Same device (VDU-VDU) group experiment scenario

Results

Behavioural indicator data

Behavioural data from 12 valid groups underwent Z-score normalisation, with trials exceeding ±3σ (0.5% of data) removed to eliminate outliers. The data were imported into SPSS for two-way multivariate variance test.

From the Sig values of each significance test, the effect of the cross-screen number on the reaction time is significant ($p = 0.00 \leq 0.05$). The effect of the cross-screen orientation on the reaction time is not significant ($p = 9.00 > 0.05$), and the effect of each factor on the accuracy rate is not significant ($p > 0.05$); The impact of the alarm level on the reaction time is significant ($p=0.00 \leq 0.05$). The impact of the number of alarms and the alarm location on the reaction time is not significant (the number of alarms $p =3.20 > 0.05$; the alarm location $p =0.27 > 0.05$), and the impact of each factor on the accuracy rate is not significant ($p > 0.05$).

By applying the multiple linear regression method, the construction of the multiple linear regression model of the alarm level and the number of cross-screens on the reaction time is statistically significant ($F=76.498$, $P< 0.05$). As shown in Table 1, the regression coefficients of the alarm level and the number of screens crossed are both statistically significant ($P < 0.05$). The coefficients of the number of screens crossed are 2.4851*10-5, indicating that the more screens crossed, the longer the reaction time and the more difficult it is to have an attention capture effect. The alarm level is a binary variable, with a low level coded as 0 and a high level coded as 1. The coefficient is -3.2762*10-5, indicating that a high alarm level has a negative impact on the reaction time and the attention capture effect is more significant. The relationship between the reaction time and the influencing factors of the alarm level and the number of screens crossed can be expressed by the multivariate linear regression model shown in Eq. (1):

Table 1: Multivariate Linear Regression Coefficients for behavioural Indicators

Model		Unstandardised coefficients		Standardised coefficient		
		B	Standard error	Beta	t	Significance
1	(constant)	1.2206E-04	.000	-	21.686	.000
	Alarm level (AL)	-3.2762E-05	.000	-.230	-6.186	.000
	Number of	2.4851E-05	.000	.403	10.813	.000

cross-screen (NCS)					

Dependent Variable：RT

$$RT = 2.4581 \times 10^{-5} \times NCS - 3.2762 \times 10^{-5} \times AL + 1.2206 \times 10^{-4} \quad (1)$$

Eye movement indicator data

Eye movement data from 12 participants (3 excluded due to low sampling rate) were collected using Tobii Glasses 2, recording number of fixations, duration of fixations, number of saccades, pupil diameter, and scanning path. Data were processed in Tobii Pro Lab with I-VT gaze filtering and aligned to trial-specific time-of-interest (TOI) windows. Outliers beyond $\pm 3\sigma$ (0.5% of data) were removed, consistent with behavioural data protocols. The data were imported into SPSS for two-way multivariate variance test.

From the Sig values of each significance test, the number of cross-screens has a significant effect on the number of eye saccades ($p = 0.05 \leq 0.05$), and has no significant effect on the number of fixations, fixation duration, and pupil diameter data (number of fixations $p = 0.25 > 0.05$; average pupil diameter $p = 2.39 > 0.05$; fixation duration $p = 3.91 > 0.05$). The cross-screen orientation had no significant effect on the eye movement indicators (the number of saccades $p = 1.37 > 0.05$; the number of fixations $p = 1.56 > 0.05$; the average pupil diameter $p = 8.90 > 0.05$; the duration of fixations $p = 2.36 > 0.05$); Due to the limited accuracy of eye movement data, the alarm location was removed from the verification of the fault alarm dimension indicators, and only the number of alarms and the alarm level were retained. The alarm level has a significant effect on the number of saccades and fixations (the number of saccades $p = 0.00 \leqslant 0.05$; the number of fixations $p = 0.00 \leqslant 0.05$), but has no significant effect on the pupil diameter data and fixation duration (the average pupil diameter $p = 8.17 > 0.05$; the fixation duration $p = 5.61 > 0.05$). The number of alarms has a significant effect on the number of fixations and fixation duration (the number of fixations $p = 0.01 \leqslant 0.05$; the fixation duration $p = 0.00 \leqslant 0.05$), but has no significant effect on the number of saccades and the average pupil diameter data (the number of saccades $p = 0.42 > 0.05$; the average pupil diameter $p = 4.20 > 0.05$).

By applying the multiple linear regression method, the multiple linear regression model of the alarm level and the number of screen crosses on the number of saccades was constructed, which was statistically significant ($F=13.702$, $P \leqslant 0.05$). As shown in Table 2, the regression coefficients of the alarm level and the number of screen crosses were statistically significant ($P \leqslant 0.05$). The coefficients of the number of screen crosses were 4.772, indicating that the more screen crosses, the more saccades, the more difficult it was for the subjects to concentrate, and they kept switching from one stimulus to another, and it became more difficult to produce an attention capture effect on a fixed target stimulus. The alarm level is a binary variable, with a low level coded as 0 and a high level coded as 1. The coefficient is -5.558, indicating that a high alarm level has a negative impact on the number of saccades. Under this condition, the subjects highly focus their attention on the target stimulus and have a higher visual search efficiency. The relationship between the number of saccades and the influencing factors of the alarm level and the number of screen crosses can be expressed by the multiple linear regression model shown in Eq. (2):

Table 2 :Multivariate Linear Regression Coefficients for Eye-tracking Indicators

Model		Unstandardised coefficients		Standardised coefficient		
		B	Standard error	Beta	t	Significance
1	(constant)	9.693	2.027	-	4.783	.000

Alarm level (AL)	-5.558	1.781	-.244	-3.120	.002
Number of cross-screen (NCS)	4.772	1.184	.316	4.030	.000

Dependent Variable: Number of eye saccades (NES)

$$NES = 4.772 \times NCS - 5.558 \times AL + 9.693 \quad (2)$$

Discussion

This study used a fault alarm awareness task to examine the effects of cross-screen interaction and fault alarm variables on behavioural and eye movement indicators, including reaction time, accuracy, fixation count, fixation duration, saccade count, pupil diameter, and scanning path. Key findings include that the number of cross-screens, alarm level, and number of alarms significantly influenced these indicators, while cross-screen orientation and alarm position did not.

The number of cross-screens negatively impacted attention capture, while alarm level positively affected it. Multivariate regression models (Eq. (1) and (2)) describe their interaction. Figure 9 shows a positive correlation between reaction time and saccades in cross-screen environments. Reaction times were shorter and fewer saccades occurred with higher alarm levels. As displays exceeded the subject's field of vision, they had to move physically to locate targets, which reduced attention capture and task efficiency, aligning with the findings on cross-screen interaction with multiple devices (Majrashi et al., 2016). High-frequency flashing alarms effectively conveyed urgency, attracting attention and prompting faster, more focused responses.

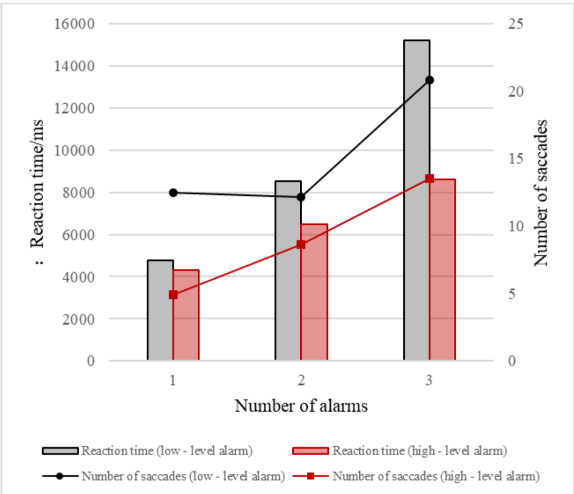

Figure 9. Response Times and Number of Saccades at High and Low Alarm Levels across Different Numbers of Screens

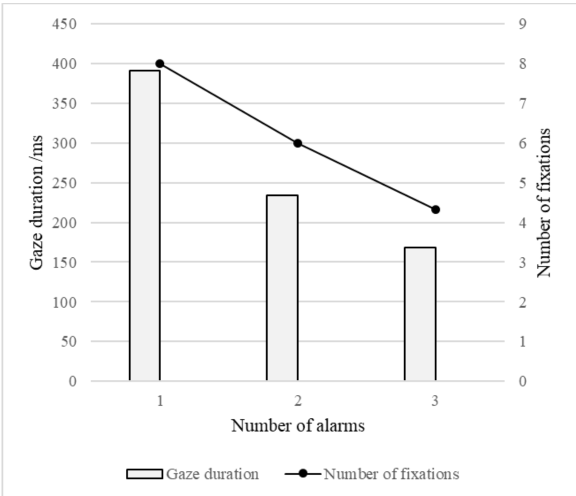

Figure 10. Number of Fixations and Duration of Fixations at Various Alarm Quantities

The effect of the number of alarms on the attention capture effect is mainly reflected in the eye movement indicators related to fixation. As shown in Figure 10, the number of fixations and the duration of fixations both decrease with the increase in the number of alarms, indicating that the more stimuli there are, the more limited the attention capture effect will be. Multiple alarms cause the subjects to be distracted, quickly shift their gaze between many potential targets, and not process a single alarm in depth. This can also be understood as the perceptual similarity between multiple targets. After discovering the first alarm, the subjects can quickly find the remaining alarms without investing too much attention resources. This is consistent with the experimental results in a single screen and is not affected by the cross-screen context (Gorbunova, 2017). The scanning path can clearly represent the annotation behaviours characteristics of the subjects in obtaining target stimulus information when completing the fault alarm visual search task. Even if all subjects are faced with similar search tasks, the scanning path guided by visual attention allocation is affected by individual differences. This difference suggests that individuals adopt different attention resource allocation strategies, or that there are differences in information processing capabilities and experience levels. Therefore, this study selected a typical subject's scanning path under different numbers of alarms for analysis, as shown in Figure 11.

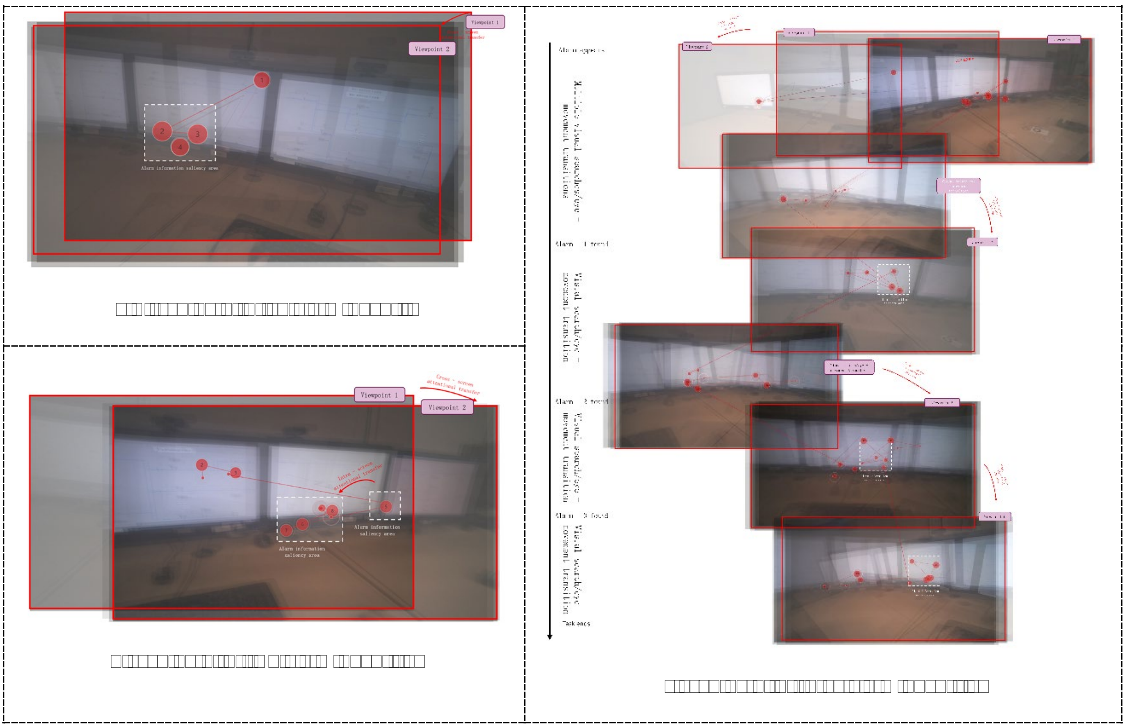

Figure 11. The scanning path of a typical subject under different alarm numbers at high alarm levels

The relevant eye movement data under each alarm number task are shown in Table 3. It can be seen that when the subjects search and respond to fault alarms, the number of fixations and eye saccades increases with the increase in the number of alarms. The fixation points are mainly distributed in the middle of the visual field. When there are multiple alarm information in the visual field, the alarm information on the screen will have a better attention capture effect, and then produce attention transfer within the screen. When the alarm information is not in the visual field, the subjects will actively turn their perspectives for visual search, which is consistent with the point that the subjects need to shift their perspectives and look at the area outside the initial visual field, resulting in a decrease in the proportion of fixation behaviours on the original area (Lavoie et al., 2018). The more fault alarms there are in the cross-screen interaction task, the more cross-screens there are, the more dispersed the fixation points are, and the more complicated the scanning path will be. When the number of alarms is large and distributed across screens, as the subjects turn their perspectives, multiple invalid information search behaviours will occur, affecting the performance of the alarm information perception task. Optimising the layout of the monitoring screen is an effective way to avoid excessive operator shifting of perspective in the cross-screen behaviours scenario design.

Table 3: Eye-tracking data for a typical subject at high alarm level across various alarm quantities

Number of alarms	Number of fixations/times	Fixation duration /ms	Number of eye saccades /times	Average pupil diameter /mm

1	4	412.25	4	3.32271
2	11	303.2727273	14	3.43180909
3	49	424.5102041	77	3.620124082

Conclusion

This research focuses on key cross-screen interaction behaviours within nuclear power monitoring systems, integrating visual attention capture mechanisms. A cross-screen interaction attention capture experimental paradigm tailored to specific task contexts is proposed. The results obtained from the experiments will facilitate a deeper understanding of the underlying mechanisms of cross-screen behaviours and cognitive processes. Additionally, this study aims to reveal the mapping relationships between interface factors and cross-screen interaction, providing empirical evidence for subsequent interface design and information presentation.

Acknowledgments

This work was supported by State Key Laboratory of Nuclear Power Safety Monitoring Technology and Equipment (K-A2021.419), the National Nature Science Foundation of China (52175469), and Jiangsu Province Nature Science Foundation of China (BK20221490).

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