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Evaluation of Digital Interface for Traditional Cultural Education based on Eye-tracking Technology

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Abstract
This study evaluates the effectiveness of digital traditional cultural education using eye-tracking technology. By analyzing participants' visual behavior, attention to key content, and cognitive load during digital learning, the study highlights both the advantages of visual and interactive design in enhancing learning outcomes and challenges like information overload. A mixed-methods approach, combining quantitative eye-tracking data and qualitative interviews, revealed insights into optimizing digital education design to improve learning experiences and outcomes.

Keywords: Eye-tracking Technology, Traditional Cultural Education, User Experience, Cognitive Load

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1.0 Introduction

With the rapid development of information technology, education has increasingly shifted to digital formats, and traditional cultural education is also being delivered through digital platforms such as museum websites and smart-tour systems (Yang et al., 2024). Although these platforms broaden access and enrich interactive presentation, their educational effectiveness is not guaranteed because unclear navigation, weak visual hierarchy, and information overload may increase cognitive load and reduce learning efficiency. Therefore, it is necessary to evaluate whether digital interfaces can support users in locating, processing, and understanding cultural information effectively.

Eye-tracking technology provides an objective approach to capturing users' visual attention and information processing during real interaction, and it has been widely applied in interface evaluation (Lu et al., 2023). Accordingly, this study evaluates the effectiveness of digital interfaces for traditional cultural education using eye-tracking technology, focusing on visual behavior, task performance, and cognitive load. The research objectives are: (1) to measure and compare users' visual behavior and interaction efficiency across different interfaces using eye-tracking and performance indicators, (2) to identify interface factors related to higher cognitive load and operational difficulty, and (3) to propose evidence-based recommendations to optimize information hierarchy, navigation, and interaction design.

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2.0 Literature Review

This study conducted a comprehensive literature review focusing on the effectiveness of digital interface design for traditional cultural education and user experience. In recent years, with the advancement of information technology, eye-tracking technology has been widely applied in fields such as education, advertising, and user interface design (Yang, 2022; Hu et al., 2025). eye-tracking data provides an objective way to understand users' visual attention distribution, information processing efficiency, and cognitive load on interfaces, which is more reliable compared to traditional user feedback (Chen et al., 2022). This research aims to leverage these findings to explore optimization paths for digital traditional cultural education interface design.

In the context of interface design and user experience, studies have indicated that clear and simple interfaces can effectively reduce users' cognitive burden and improve learning efficiency (Kim et al., 2021; Shi, Ono, & Li, 2025). For example, simplified icon designs and unified color themes can help users quickly locate key information and reduce search difficulty (Johnson et al., 2020). However, other studies have pointed out that overly complex interface designs may lead to information overload, preventing users from effectively accessing key content and consequently reducing learning outcomes (Zhang et al., 2020). Recent studies consistently suggest that reasonable digital interface design is crucial for learners' knowledge acquisition and experience, and that eye-tracking technology can help identify areas of user attention, thereby providing scientific basis for interface optimization.

The digitization of traditional cultural education is an important trend in recent years. Digital methods of showcasing traditional cultural heritage can not only increase learners' interest but also enhance their learning outcomes through interaction (Yang et al., 2024; Menzel et al., 2022). However, in terms of effectively conveying cultural meaning while avoiding excessive cognitive load, existing studies show significant disagreements and inadequacies (Kim et al., 2022). For instance, some studies have found that excessive visual information and complex symbolic designs increase users' cognitive load (Zhang & Cui, 2022), while culturally significant symbolic design can enhance users' emotional engagement and cultural understanding (Yang et al., 2021).

Based on these existing studies, this literature review systematically collected both classical and recent research findings to provide a comprehensive overview of the existing knowledge. Firstly, it clarified the role of eye-tracking technology in assessing user attention and cognitive load (Castro et al., 2024; Zhang et al., 2025). Through a review of related interface design studies, it identified key design factors that can enhance learning efficiency, such as the clarity of symbols, cultural attributes of colors, and simplicity of information organization (Huang, 2020; Lian et al., 2023). Secondly, the review critically analyzed existing literature, highlighting that most research has focused on general interface design optimization, whereas research specifically addressing traditional cultural education is lacking, especially in combining modern digital technology with traditional cultural elements (Yang & Su, 2021; Shi, Zhou, & Ono, 2025).

In summary, in designing digital interfaces for traditional cultural education, it is essential to focus on the visual clarity of cultural symbols, the cultural alignment of color schemes, and the simplicity and logicality of information presentation (Chemerys & Ponomarenko, 2022; Yang et al., 2024). These design elements can reduce users' cognitive load and effectively convey cultural meanings. Moreover, the application of eye-tracking data provides an objective perspective that enhances the persuasiveness and practical value of the research findings (Ugwitz et al., 2022; Tupikovskaja-Omovie, 2025). Existing studies have provided a theoretical foundation and empirical evidence for this research.

3.0 Methodology

3.1 Participants

The study involved 46 participants, all of whom were undergraduate students at Huazhong Agricultural University in Wuhan, Hubei, China. The Chinese university student population is a key target audience for digitalized traditional cultural education, which is why this group was selected to better reflect the applicability and effectiveness of the digital education interface for the target users.

3.2 Experimental Design

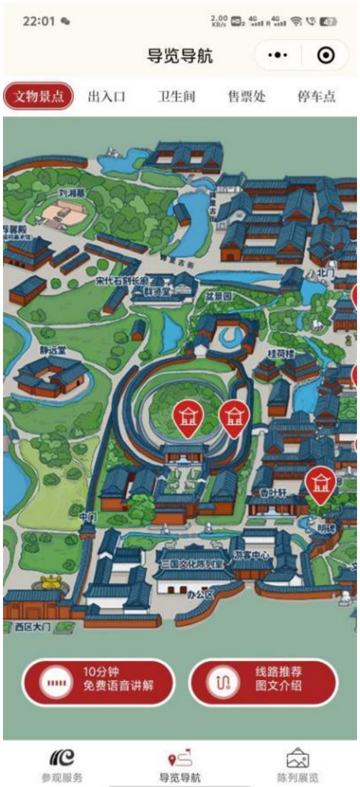
This study employed an experimental approach using eye-tracking technology to analyze user behavior while interacting with a digital interface for traditional cultural education (Kim et al., 2021). The experimental materials included four representative digital cultural education platforms: Wuhou Temple Museum, Lishanyuan Cultural District, Gusu Ancient City, and Smart Tour of Mount Wutai. These platforms exhibit diverse interface styles and interactive designs, representing the current diversity in digital traditional cultural education.

Table1. Stimulus materials coding

Sample Code	Sample Name	Region in China
A	Wuhou Temple Museum	Southern
B	Lishanyuan Cultural District	Northern
C	Gusu Ancient City	Southern
D	Smart Tour of Mount Wutai	Northern

(Source:Developed by the researcher)

Samplea:Wuhou temple museum	Sampleb:Lishanyuan cultural district



Samplec:Gusu ancient city

Sampled:Smart tour of mount wutai

Fig. 1: Stimulus material sample

In the experimental procedure, researchers first introduced participants to the study's objectives and procedures, informing them of relevant precautions. All participants signed informed consent forms. During the experiment, participants wore Tobii Pro Glasses, and researchers calibrated the equipment to ensure accuracy in eye-tracking data (Chen et al., 2022). The experimental tasks covered multiple aspects, including browsing cultural modules, searching for specific information, performing interactive tasks, and answering related questions. Participants were required to browse different cultural education modules, such as Wuhou Temple Museum, Lishanyuan Cultural District, Gusu Ancient City, and Smart Tour of Mount Wutai, to familiarize themselves with the interface layout and functions. During information search tasks, participants followed experimental guidelines to locate cultural backgrounds or artifact descriptions, evaluating the efficiency and effectiveness of the interface for information retrieval (Yin & Neyens, 2024). Additionally, participants interacted with the interface by playing audio descriptions, sharing information, and switching views to assess the usability of interactive features. While browsing and interacting, participants answered questions related to the content to evaluate their understanding of the learning material and assess the interface's effectiveness in knowledge delivery (Yang et al., 2024). Throughout the experiment, eye-tracking devices recorded participants' fixation duration, fixation count and revisits count, and this data was collected using Tobii Pro Glasses Controller software (Zhang et al., 2020). At the same time, three task performance metrics, task completion time, error rate and help request rate, were also recorded. After completing all tasks, structured interviews were conducted to further understand participants' experiences and difficulties encountered during the tasks. Additionally, researchers analyzed eye-tracking videos to identify specific problems users faced during interface use (Yang et al., 2024).

3.3 Evaluation Method

The learning effectiveness of the interface was comprehensively evaluated using eye-tracking, performance evaluation, and supplementary evaluation methods (Castro et al., 2024). eye-tracking recorded users' eye movement paths to analyze fixation points, fixation duration, and revisits count, providing a quantitative measure of users' cognitive load and difficulties during operation (Kim et al., 2022). Performance evaluation involved metrics such as task completion time, error rate, and help request rate to assess the interface's effectiveness and efficiency (Lu et al., 2023). Supplementary evaluation methods, including post-experiment structured interviews and eye-tracking video analysis, complemented the quantitative evaluation to provide deeper insights into the user experience (Yang et al., 2024).

The evaluation model was designed to provide a comprehensive assessment of the learning effectiveness of the interface. The evaluation dimensions included efficiency, effectiveness, and learnability (Lu et al., 2023). Metrics such as fixation duration and fixation count were used to evaluate efficiency, where shorter fixation duration and fewer fixation counts indicated higher information transmission efficiency (Kim et al., 2021). Effectiveness was assessed using task completion time and error rate, where shorter completion times and fewer errors indicated that the interface was well-designed and easy for users to operate (Huang, 2020; Zhang & Cui, 2022). Learnability was assessed using revisits count and help request rate, where fewer revisits and help requests indicated that the interface was easy to understand and use (Kim et al., 2022; Yang et al., 2024).

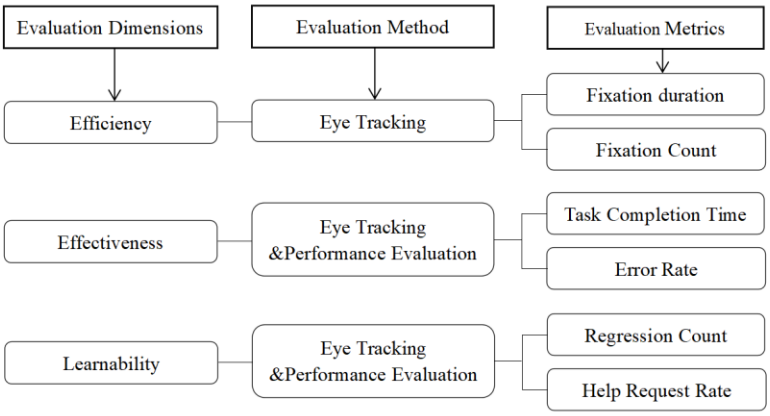


Fig. 2: Evaluation model
(Source:Developed by the researcher)

3.4 Data Analysis

The study combined eye-tracking data with user subjective feedback and used SPSS software for quantitative analysis (Menzel et al., 2022). Meanwhile, qualitative analysis of eye-tracking videos supplemented the quantitative data to deeply explore the problems and challenges users encountered during interface operation (Yang et al., 2024). Through eye-tracking video, we observe the user's visual behavior and operation process when operating the interface, capture the fluency of saccades, fixation areas (staying areas) and markings of key events, and gain a deep understanding of the user's natural operation habits and usability issues of interface design(Goncalves et al., 2022).

Structured interviews were also conducted to collect users' subjective experiences and feedback, which were integrated with eye-tracking data to gain a comprehensive understanding of the user experience (Kim et al., 2021). For instance, if eye-tracking data showed frequent revisits in certain areas, and users mentioned difficulties understanding these areas during interviews, it became clear that these design elements have a high cognitive load, resulting in reduced learning effectiveness (Zhang et al., 2020).

4.0 Results

The experimental results showed significant differences in users' visual behavior across different digital interfaces.

Table 2. Evaluation metrics data

No.	FD	FC	RC	TCT	ER	HRR
	Fixation Duration （Second）	Fixation Count	Revisits Count	Task Completion Time （Second）	Error Rate	Help Request Rate
A	5.123± 0.732	17.652± 2.134	3.543± 0.859	23.845± 3.621	0.630± 0.312	0.270± 0.150
B	4.876± 0.698	17.130± 2.056	3.217± 0.893	22.568± 3.492	0.522± 0.289	0.209± 0.127
C	5.452± 0.785	18.304± 2.375	3.826± 0.912	24.958± 3.948	0.754± 0.399	0.291± 0.168
D	4.978± 0.714	17.826± 2.178	3.370± 0.873	23.256 ± 3.712	0.610± 0.334	0.235± 0.139

(Source:Developed by the researcher)

4.1 Boxplot Analysis

The box plot shows that group B has high stability in multiple metrics and high data concentration, indicating that its interface design has advantages in information acquisition and operation efficiency. In contrast, group C has a wider data distribution and more outliers, especially in metrics such as fixation count, revisits count and error rate, indicating that group C has a large cognitive load and operational difficulty in interface design. Groups A and D perform similarly to group B, but are slightly inferior to group B in some metrics (such as task completion time and fixation count).

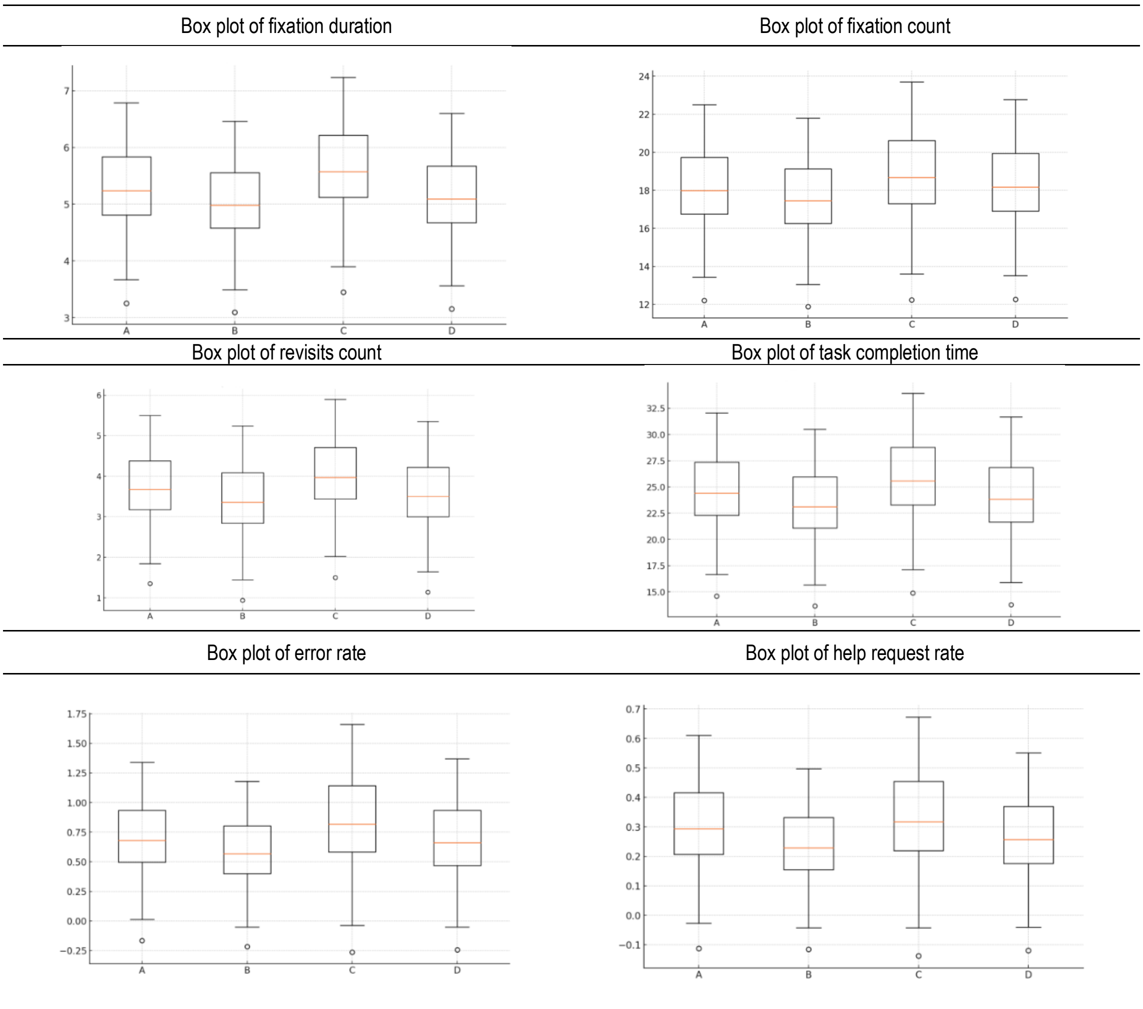


Fig. 3: Box plot of metrics
(Source:Developed by the researcher)

4.2 ANOVA

A one-way ANOVA was used to test the significance of differences between different sample groups across various metrics. The results showed that except for Fixation Count, which had no significant difference, other metrics had significant differences ($P<0.05$).

Table 3. One-way anova for evaluation metrics

Metrics	M/SD	A	B	C	D	F-value	P-value
Fixation Duration	M	5.123	4.876	5.452	4.978	5.402	0.001
	SD	0.732	0.698	0.785	0.714		
Fixation Count	M	17.6521	17.130	18.3042	17.826	2.255	0.084
	SD	2.134	2.056	2.375	2.178		
Revisits Count	M	3.543	3.217	3.826	3.37	4.011	0.009
	SD	0.859	0.893	0.912	0.873		
Task Completion Time	M	23.845	22.568	24.958	23.256	3.449	0.018
	SD	3.621	3.492	3.948	3.712		
Error Rate	M	0.630	0.522	0.754	0.610	3.726	0.012
	SD	0.312	0.289	0.399	0.334		
Help Request Rate	M	0.270	0.209	0.291	0.235	2.833	0.034
	SD	0.15	0.127	0.168	0.139		

(Source:Developed by the researcher)

4.3 Post-hoc Analysis

Following the ANOVA test, multiple comparison analysis was conducted to determine which specific sample groups had significant differences. The results indicated that Sample C had significant differences compared to other samples in multiple metrics, particularly fixation count and task completion time, further confirming deficiencies in Sample C's design.

Table 4. Post-hoc analysis for evaluation metrics

Evaluation Metrics	Sample	P-value
Fixation Duration	A vs B	0.108
	A vs C	0.033
	A vs D	0.344
	B vs C	0.000
	B vs D	0.505
	C vs D	0.002
Fixation Count	A vs B	0.254
	A vs C	0.155
	A vs D	0.703
	B vs C	0.011
	B vs D	0.129
	C vs D	0.296
Revisits Count	A vs B	0.079
	A vs C	0.127
	A vs D	0.345
	B vs C	0.001
	B vs D	0.408
	C vs D	0.014
Task Completion Time	A vs B	0.099
	A vs C	0.151
	A vs D	0.446
	B vs C	0.002
	B vs D	0.373
	C vs D	0.029
Error Rate	A vs B	0.125
	A vs C	0.078
	A vs D	0.776
	B vs C	0.001
	B vs D	0.211
	C vs D	0.041
Help Request Rate	A vs B	0.048
	A vs C	0.493
	A vs D	0.254
	B vs C	0.008
	B vs D	0.397
	C vs D	0.069

(Source:Developed by the researcher)

4.4 Effect Size Calculation

Effect size was calculated to quantify the practical significance of the differences between groups. The results showed large Cohen's d effect sizes for Sample C in terms of fixation count and task completion time, indicating that the differences between Sample C and other samples had strong practical significance, further supporting the impact of interface design.

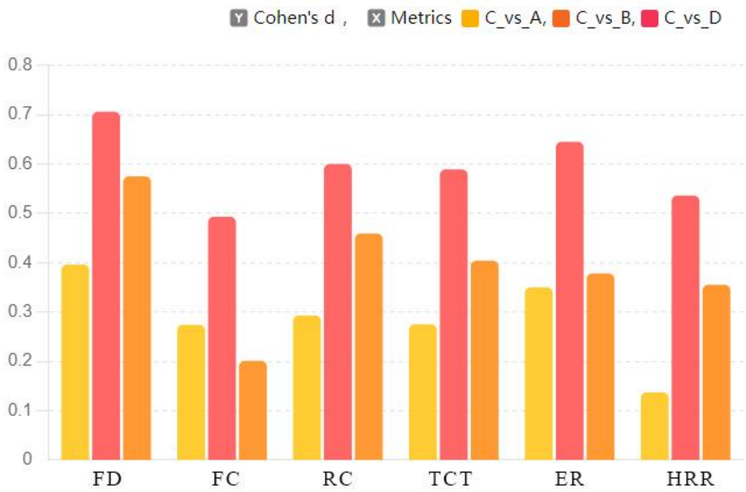


Fig. 4: Cohen's d effect size
(Source:Developed by the researcher)

4.5 Regression Analysis

To further understand the impact of different metrics on users' task completion time, a linear regression analysis was conducted. In summary, Revisits Count and Fixation Count are the most important factors affecting Task Completion Time, which is consistent with the results that Group C showed greater volatility and discreteness in the effect size analysis. When Group C users completed the task, their frequent look back and fixation may mean that they had a greater cognitive burden when understanding the interface information or performing operations, which led to a longer Task Completion Time.

Table 5. Linear regression model results

Variable	Regression Coefficient	Standard Error	t-Value	P-Value	Confidence Interval Lower Limit	Confidence Interval Upper Limit
Const	-0.1991	5.97e-16	-3.34e+14	0.000	-0.199	-0.199
Fixation Duration	0.4487	2.01e-16	2.24e+15	0.000	0.449	0.449
Fixation Count	0.9972	4.8e-16	2.08e+15	0.000	0.997	0.997
Revisits Count	1.0206	1.73e-15	5.9e+14	0.000	1.021	1.021
Error Rate	0.6297	1.31e-15	4.82e+14	0.000	0.630	0.630
Help Request Rate	0.2704	5.65e-16	4.78e+14	0.000	0.270	0.270

(Source:Developed by the researcher)

Fig. 5: Linear regression histogram
(Source:Developed by the researcher)

4.6 Multivariate Analysis

Through multivariate analysis, such as principal component（PCA） analysis, latent patterns among different sample groups were identified. The results revealed that Sample C's performance on several principal components significantly differed from other samples, suggesting deficiencies in its interface design, particularly in terms of information complexity and symbol layout. These differences may be the primary reason for Sample C's increased operational difficulties and cognitive load.

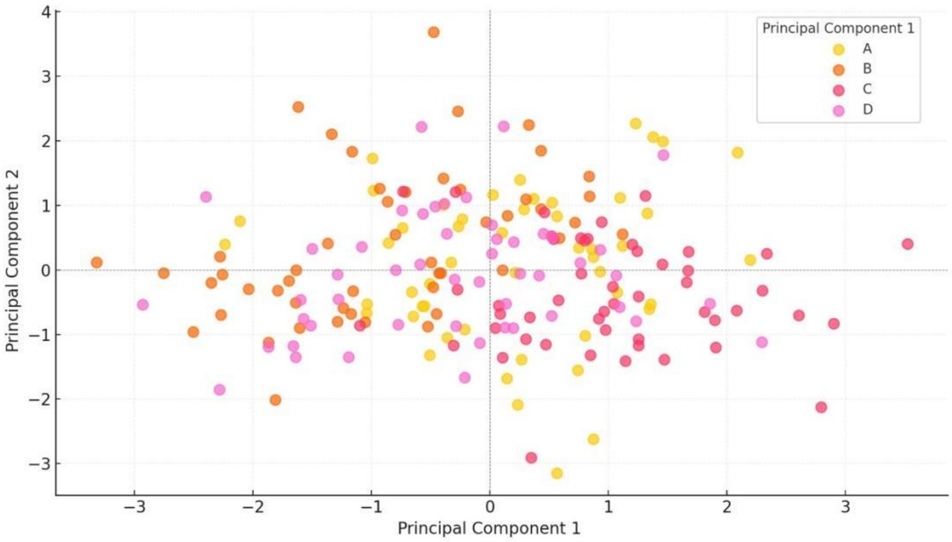


Fig. 6: Multivariate analysis scatter plot
(Source:Developed by the researcher)

5.0 Discussion

Combining quantitative and qualitative evidence, the study indicates that efficient interface design can effectively reduce users' cognitive load and enhance learning outcomes. Sample B performed best because its interface was concise and visually organised, with clear symbols and a rational layout that enabled users to locate targets quickly and complete tasks in a shorter time. In particular, the appropriate symbol size, high recognisability, and logically distributed layout helped shorten visual search paths, which in turn reduced unnecessary eye movements and fixation time, highlighting the strong relationship between interface design, information processing efficiency, and learning performance.

The advantages of Sample B can be summarised in several interrelated design strengths. First, it adopted high-contrast colours and straightforward symbols, supporting fast recognition while avoiding the two extremes of symbols being either too dominant or too subtle to identify. Second, the interface style remained consistent in colour and symbol standards across pages, which reduced cognitive burden during repeated operations and information retrieval. Third, the navigation structure was simple and transparent, allowing users to reach needed information with fewer detours and less backtracking, thereby improving overall task efficiency. In addition, Sample B integrated cultural elements with visual aesthetics through flat and geometric icon design and dynamic modules, enhancing cultural recognition and emotional engagement without disrupting usability. The unified colour theme, typically a clean background with low-saturation tones and high-contrast emphasis for key elements, helped guide attention toward important information. Finally, its hierarchical layout and relatively centralised placement of core functions, supported by card-based modules, improved learnability and overall interface clarity. The hand-drawn map style and 2.5D scenic presentation further strengthened visual-cultural consistency and cultural atmosphere, contributing to engagement while maintaining readability.

By contrast, Sample C presented several design problems that likely increased operational difficulty and cognitive load. Users faced small symbols with insufficient contrast, and the interface contained excessive information, creating visual clutter and information overload. Dense symbol areas and weak hierarchy made it harder to identify functional modules, which contributed to disorientation and frequent returns for checking. Accordingly, improvement directions for Sample C include enlarging symbols and enhancing contrast, simplifying information by reducing non-essential content and prioritising key learning materials, redistributing symbols more evenly to avoid local density, and clarifying navigation paths to support stable wayfinding. Building a clearer hierarchical layout with content segmentation can further reduce comprehension difficulty and improve learnability. In addition, a culturally oriented colour scheme, such as the use of traditional Chinese colour references, may enhance cultural identity and satisfaction, provided that contrast and readability are preserved. The adoption of a consistent hand-drawn map style and 2.5D form can also be considered to strengthen cultural atmosphere, but it should serve, rather than compete with, functional clarity.

Structured interviews further supported these patterns. Participants generally described Sample B as easy to use, with clear navigation and accessible information that reduced the need for repeated searching and confirmation, resulting in a more positive experience. In contrast, users of Sample C frequently reported information overload and chaotic layout, which caused them to lose direction and repeatedly return to verify information, thereby weakening the experience.

Eye-tracking recordings provided convergent evidence for the quantitative findings. Users interacting with Sample C tended to show poorer saccade fluency, more fixation areas, and more complex scan paths, especially in regions with dense symbols and layered information, indicating difficulty in understanding and operating these areas. This visual behaviour is consistent with prolonged task completion time and increased error risk. Conversely, Sample B showed more focused fixation behaviour with fewer revisits, and its symbols and information were easier to identify and interpret, suggesting that the design was better aligned with users' cognitive processing needs. Overall, the agreement between eye-tracking observations and subjective feedback reinforces the importance of clear symbols, coherent hierarchy, simplified information structure, and navigational transparency in improving learning efficiency, reducing cognitive load, and enhancing user experience in digital traditional cultural education interfaces.

6.0 Conclusion

This study evaluated four digital interfaces for traditional cultural education using eye-tracking technology and user feedback, and the results consistently indicate that interface design directly shapes visual attention allocation, information processing efficiency, and cognitive load. Overall, concise layouts, clear symbol systems, and transparent navigation support faster task completion and better learning experience, whereas dense information and ambiguous wayfinding increase operational difficulty and impair learning outcomes. In particular, the comparative pattern suggests that Sample B better fits users' cognitive expectations, while Sample C shows typical usability barriers that can be diagnosed through eye-tracking evidence. Nevertheless, the generalisability of these findings is constrained by methodological limitations, most notably the relatively small sample size and the homogeneity of participants, as all users were recruited from a single university. This single-institution sampling may not adequately represent broader populations with different cultural backgrounds, age groups, digital literacy levels, or learning motivations, and thus the observed patterns should be interpreted as indicative rather than fully generalisable.

To move beyond general conclusions, the findings also imply concrete, metric-linked design directions for interfaces similar to Sample C. Higher Revisits Count (RC) together with long Task Completion Time (TCT) indicates unclear navigation and weak wayfinding cues, therefore interface redesign should strengthen global navigation, location indicators, and stable return paths to reduce backtracking. Higher Fixation Count (FC) aligned with long TCT reflects inefficient visual search caused by small symbols, low contrast, and weak hierarchy, therefore symbols should be enlarged, contrast increased, and key functions prioritised through a clearer visual hierarchy and more rational spatial distribution to shorten search paths. When higher Error Rate (ER) and Help Request Rate (HRR) occur alongside high RC, it suggests poor learnability and insufficient feedback, therefore interaction prompts and immediate state feedback should be improved and error-prevention mechanisms added to support recovery. Future research should not only expand the sample size but also diversify participant sources across multiple universities or non-student user groups, and it should conduct redesign-based validation, such as controlled before–after tests or A/B testing on Sample C-type interfaces, to examine whether targeted changes lead to measurable reductions in RC, FC, TCT, ER, and HRR while improving learning-related outcomes.

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