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EVALUATION OF CULTURAL TOURISM SMART GUIDE MAP INTERFACE BASED ON VISUAL COGNITIVE CHARACTERISTICS

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Abstract:

The cultural tourism smart guide is an essential tool for enhancing visitor experiences, especially in the age of smart tourism. However, gaps exist in the usability of interactive sharing features within these maps, particularly regarding how they affect user satisfaction and efficiency. This study employed Eye Tracking technology to evaluate the usability of interactive features in cultural tourism guide maps. The methodology involved Eye Tracking data collection from 46 participants across four representative guide map interfaces, followed by a statistical analysis based on visual cognitive characteristics. The key findings revealed significant differences in user attention and efficiency across the samples, with one particular map interface showing notably poorer performance in terms of fixation count, task completion time, and error rate. Research on visual attention capacity significantly impacts user interaction efficiency. The data also emphasize the importance of designing interfaces that reduce cognitive load by simplifying visual elements and optimizing information presentation and provide valuable insights for optimizing smart guide map interfaces for cultural tourism.

Keywords:

Cultural Tourism Smart Guide, Interface Evaluation, Map Interface, Visual Cognitive Characteristics, Visual Attention

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Introduction

Cultural tourism guide maps are indispensable tools for enhancing tourists' experiences by providing intuitive route planning and attraction information. However, designing interfaces that effectively integrate cultural elements and ensure usability remains challenging. Issues such as information overload, lack of intuitive interactivity, and inconsistency in visual design often hinder user experience and satisfaction, especially in the context of smart tourism (Bai, Law, & Wen, 2021; Zhao, 2021). These challenges highlight the need for systematic usability evaluation and optimization. With advancements in smart tourism, interactive sharing features have become a pivotal component of modern guide maps, directly influencing user interaction efficiency and satisfaction. While previous studies have investigated general usability issues, few have focused on how visual cognitive characteristics interact with cultural elements in map interfaces. Eye Tracking technology provides an innovative approach to capturing user visual behavior, offering scientific insights into usability optimization (Diego-Mas et al., 2019; Rezae et al., 2020).

This study aims to bridge these gaps by evaluating the usability of interactive sharing features in cultural tourism guide maps, focusing on efficiency, effectiveness, and learnability. The findings will contribute to designing smarter, culturally sensitive interfaces that enhance user satisfaction and promote the development of smart tourism (Gretzel et al., 2020; Munjal, 2021).

Literature Review

Theories of Efficiency, Effectiveness, and Learnability

Interface usability is commonly assessed through the theoretical dimensions of efficiency, effectiveness, and learnability. Efficiency measures the speed at which users complete tasks and is reflected in metrics such as fixation duration and fixation count. Shorter fixation durations and fewer fixations indicate that users can process information quickly and locate targets efficiently (Diego-Mas et al., 2019). Effectiveness focuses on task completion accuracy and success rates, emphasizing the interface's intuitiveness. Metrics like task completion time and error rates are central to measuring effectiveness (Kim et al., 2022). Learnability examines how easily users can adapt to a new interface, often assessed using regression count and help request rate. Lower values in these metrics indicate a user-friendly design that supports smooth and independent user interaction (Joseph & Murugesh, 2020).

These theoretical perspectives provide a comprehensive framework for evaluating user performance and experience, particularly when assessing interfaces with interactive and visually complex features like cultural tourism smart guide maps.

Application of Eye Tracking Technology in Human-Computer Interaction

Eye Tracking technology records and analyzes user eye movements, providing detailed data on visual attention and behavior. It is widely used in human-computer interaction to optimize interface design by identifying user focus points and areas of confusion, which enables adjustments to layout and information presentation for improved user experience (Souza et al., 2022; Szekely et al., 2023). Eye Tracking is instrumental in usability testing, as it allows for the quantitative assessment of user performance in task completion through metrics such as fixation count, regression paths, and fixation duration (Johnson, Smith, & Peterson, 2020).

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In advertising and marketing, it evaluates the visual appeal and effectiveness of advertisements by analyzing fixation points and times, providing insights for design optimization (Matulewski et al., 2023). In education and training, it assesses student attention distribution to enhance teaching methods, while in medical research, it aids in diagnosing conditions such as autism and ADHD by analyzing eye movement patterns (Yang, Su, & Shen, 2021). However, its application in evaluating cultural tourism smart guide maps, particularly with interfaces involving complex cultural and visual elements, remains limited.

Application of Eye Tracking Technology in Interface Usability Evaluation

Eye Tracking technology evaluates interface usability by analyzing user visual behavior during interaction. Metrics such as fixation duration and count reveal attention distribution and efficiency in locating interface elements. Regression count highlights user difficulties in navigation, while task completion time measures operational efficiency. Eye Tracking provides objective data to identify usability issues and improve design (Rezae et al., 2020; Zhang & Cui, 2022). For example, in mobile app usability testing, it has identified design flaws that hinder operational fluency, enabling targeted optimizations (Joseph & Murugesh, 2020).

Although Eye Tracking is widely applied in fields like e-commerce and healthcare, its integration with cultural usability studies is less common. Current research focuses on specific interface features, often overlooking the comprehensive impact of cultural elements on user interaction and satisfaction. This gap underscores the need for studies that bridge cultural and usability perspectives to enhance user experience in smart tourism contexts.

Challenges in Cultural Tourism Smart Guide Maps

Cultural tourism smart guide maps must balance the incorporation of cultural elements with interface usability. Excessive visual complexity or lack of intuitive features can lead to higher cognitive load, longer task completion times, and lower user satisfaction (Rezae et al., 2020). Additionally, inconsistent interactivity and insufficient emphasis on cultural elements may limit the interface's appeal and effectiveness. These challenges highlight the need for systematic usability evaluation to ensure that cultural and functional objectives are achieved in tandem. Eye Tracking provides a valuable method for addressing these challenges by revealing how users interact with such interfaces, offering data-driven insights for optimization.

Methods

Sample Coding

To ensure the representativeness and broad applicability of the study results, four representative user-friendly products with different interface styles were selected as the experimental stimuli. These products are among the most popular cultural tourism destinations in northern and southern China and embody typical regional cultural characteristics. The four products were Wuzhen Cultural Tourism Smart Guide, Nanjing Presidential Palace Guide, Travel to Jiayuguan, and Tracing the Smart Tour of Yuelu Academy, as shown in Table 1.

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Table 1: Experimental Samples

Sample Code	Sample Name	Region in China
A	Wuzhen Cultural Tourism Smart Guide	Southern
B	Nanjing Presidential Palace Guide	Northern
C	Travel to Jiayuguan	Southern
D	Smart Tour of Yuelu Academy	Northern

Based on the different basic elements, map styles, layout characteristics, and information organization methods in the main interface of smart cultural tourism guides, four representative samples were selected as experimental materials. These samples are named: Wuzhen Cultural Tourism Smart Guide(A), Nanjing Presidential Palace Guide (B), Travel to Jiayuguan (C), and Smart Tour of Yuelu Academy(D).

Usability Evaluation Model

This study selected efficiency, effectiveness, and learnability as the attributes for evaluating interface usability. These attributes comprehensively reflect the user performance and experience when using cultural tourism guide maps (Diego-Mas et al., 2019). Six metrics were chosen to evaluate the interactive sharing features of the cultural tourism guide maps. These metrics can quantify the users' visual behavior and operational performance when using guide maps. The evaluation model is illustrated in Figure 1.

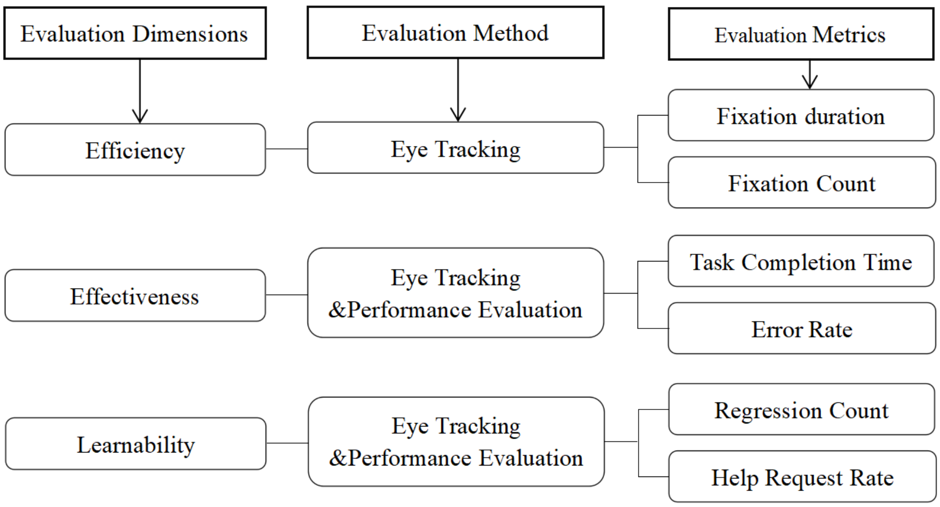

Figure 1: Usability Evaluation Model

Efficiency measures the speed at which users complete tasks. Efficiency was assessed using the following metrics: Fixation duration - The time a user spends fixating on a specific point. Shorter fixation durations indicate that users can quickly understand and process information. Fixation count - Number of fixations within a specific area. Fewer fixations indicate that users can quickly find the required information (Rezae et al., 2020).

Effectiveness measures the accuracy and completeness of task completion. Effectiveness was assessed using the following metrics: Task completion time - The total time from the start of an operation to the completion of a specific task. Shorter task completion times indicate more efficient task performance (Kim et al., 2022). Error rate - Number of errors made by users

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during task completion. Lower error rates indicate intuitive interface design and correct user operations.

Learnability measures the difficulty of learning and ease of use of the interface. Learnability was assessed using the following metrics: Regression count - The number of times a user returned to a previous fixation point while browsing the interface. Fewer regressions indicate a clear interface design and smooth navigation (Joseph & Murugesh, 2020). Help request rate - The number of times a user requests help during task completion. Lower help request rates indicate a user-friendly interface that allows users to complete tasks independently.

Participants

When selecting the experiment participants, factors such as age, gender, and educational background were considered. Because the experiment involved experiencing mobile products and completing specific tasks based on the interface content, the participants included 46 current undergraduate, graduate, and doctoral students, comprising 23 males and 23 females aged between 18 and 27 years, with an average age of 23.5 years. None of the participants had any prior experience with the samples used in the experiment (Yang & Su, 2021).

Experimental Instruments and Environment

The experiment was conducted in a laboratory using Tobii Pro Glasses2 eye tracking instrument to record the participants' eye movement data. The lighting in the experimental environment was moderate, ensuring that the participants could complete the experimental tasks comfortably (Szekely et al., 2023).

Experimental Design

Sample A: Locate Fengxian Temple and share the attraction with a WeChat friend. Click WeChat and send a button to confirm.
Sample B: Locate Baohe Hall and share the attraction with a WeChat friend. Click WeChat and send a button to confirm.
Sample C: Locate Baiyun Pavilion and share the attraction with a WeChat friend. Click WeChat and send a button to confirm.
Sample D: Locate Pit No. 3 and share the attraction with a WeChat friend. Click WeChat and send a button to confirm.

Data Collection

During the experiment, data on fixation duration, fixation count, regression count, task completion time, error rate, and help request rate were recorded for each participant (Diego-Mas et al., 2019).

Discussion

Data analysis is done in four steps: ANOVA provides basic information on the metrics of each group, showing the means and standard deviations. Determine significant differences between groups across multiple metrics (Sweller, Ayres, & Kalyuga, 2021). Post-hoc analysis identifies specific group differences. The effect size calculation quantifies the differences between group C and other groups, showing very significant differences in error rate and help request rate (Szekely et al., 2023). Multivariate analysis (PCA) identified underlying patterns between

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groups, revealing distinct behavioral patterns for group C compared to the other groups (Szwarc et al., 2023).

Table 2: Evaluation Indicators 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	5.771 ± 0.852	18.300 ± 2.150	5.173 ± 0.811	5.832 ± 0.446	0.00± 0.000	0.000± 0.000
B	6.221 ± 0.931	17.890 ± 2.060	4.901 ± 0.653	5.853 ± 0.472	0.00± 0.000	0.000 ± 0.000
C	6.372 ± 0.873	19.430 ± 2.380	5.401 ± 0.755	6.063 ± 0.439	0.22± 0.053	0.183 ± 0.057
D	5.873 ± 0.690	18.060 ± 2.170	4.998 ± 0.708	6.082 ± 0.468	0.00± 0.000	0.000 ± 0.000

ANOVA
An ANOVA was conducted on various metrics for samples A, B, C, and D, as shown in Table 3. Means and standard deviations of various metrics across different groups. The results indicated that sample C exhibited significant fluctuations in fixation duration, fixation count, regression count, and task completion time, with higher error rates and help request rates compared to the other groups; the results indicated significant differences in fixation duration, fixation count, regression count, and task completion time among the four samples ($P < 0.05$). Sample C has higher error and help request rates than the other samples, where these rates are 0.

Table 3: One-Way ANOVA for Evaluation Metrics

Evaluation Metrics	M/SD	A	B	C	D	F-value	P-value
Fixation Duration	M	5.771	6.221	6.372	5.873	5.238	0.002
	SD	0.852	0.931	0.873	0.690		
Fixation Count	M	18.300	17.890	19.430	18.060	4.607	0.004
	SD	2.150	2.060	2.380	2.170		
Regression Count	M	5.173	4.901	5.401	4.998	4.115	0.007
	SD	0.811	0.653	0.755	0.708		
Task Completion Time	M	5.832	5.853	6.063	6.082	3.922	0.010
	SD	0.446	0.472	0.439	0.468		
Error Rate	M	0.000	0.000	0.224	0.000	/	/
	SD	0.000	0.000	0.053	0.000		
Help Request Rate	M	0.000	0.000	0.183	0.000	/	/
	SD	0.000	0.000	0.057	0.000		

Post-hoc Analysis
Multiple comparisons were conducted for various metrics across Samples A, B, C, and D. Because the error rate and help request rate for groups other than C were zero and, therefore,

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lacked analytical value, these metrics were not included in the table. The results are presented in Table 4.

Table 4: One-Way ANOVA Multiple Comparison Analysis for Evaluation Metrics

Evaluation Metrics	Sample	P-value
Fixation Duration	A vs B	0.011
	A vs C	0.000
	A vs D	0.562
	B vs C	0.390
	B vs D	0.049
	C vs D	0.005
Fixation Count	A vs B	0.371
	A vs C	0.014
	A vs D	0.600
	B vs C	0.000
	B vs D	0.711
	C vs D	0.003
Regression Count	A vs B	0.077
	A vs C	0.138
	A vs D	0.254
	B vs C	0.001
	B vs D	0.527
	C vs D	0.009
Task Completion Time	A vs B	0.826
	A vs C	0.016
	A vs D	0.009
	B vs C	0.029
	B vs D	0.017
	C vs D	0.842

Statistical results indicated significant differences between group C and the other groups in terms of fixation duration, fixation count, regression count, and task completion time, suggesting that group C's performance on these metrics was markedly different. The error rate and help request rate for group C were significantly higher than those for the other groups, indicating that group C made more errors and needed more help during the experiment. This suggests that group C exhibited significantly different behavioral patterns than the other groups.The results showed that sample C differed significantly from the other groups across multiple metrics, especially fixation duration and fixation count.

Effect Size Calculation

Based on the results of the post-hoc analysis, Cohen's d effect size was calculated to quantify the differences between Group C and the other groups and to further understand the practical significance of these differences. See Table 5 and Figure 2.

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Table 5: Combined Effect Sizes (Cohen's d) for Various Metrics

Code	Metrics	C vs A	C vs B	C vs D
FD	Fixation Duration	0.463	-0.003	0.558
FC	Fixation Count	0.630	0.703	0.685
RC	Regression Count	0.479	0.953	0.572
TC	Task Completion Time	0.461	0.851	0.027
ER	Error Rate	6.541	6.541	6.541
HR	Help Request Rate	5.332	5.332	5.332

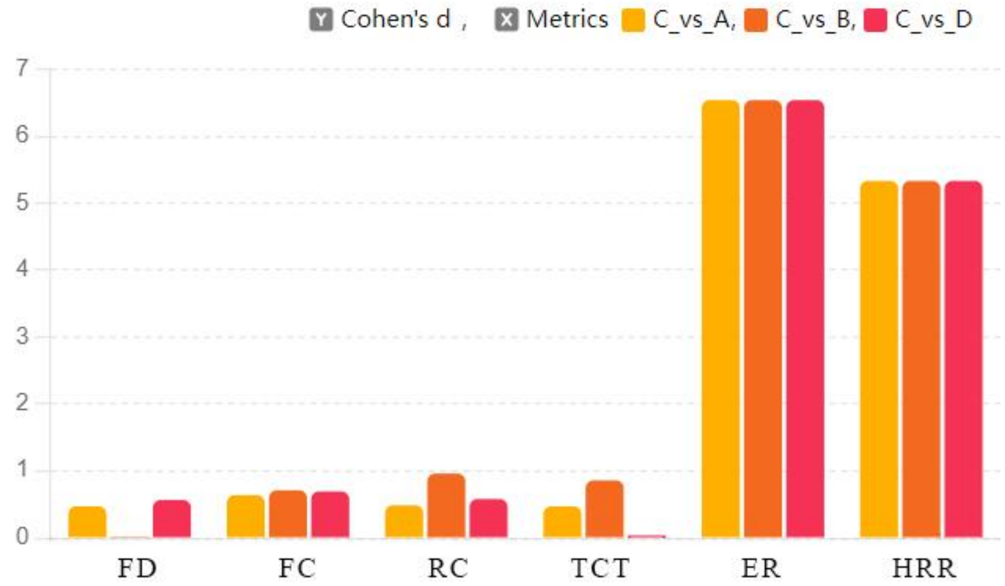

Figure 2: Cohen's D Effect Sizes By Metric

The effect size of Group C and other groups on Fixation Duration ranges from 0.463 to 0.558, which is a medium effect size. This shows that users in Group C spend a longer time looking for target information. This may be due to the fact that the visual cues of the target elements of the interface are not prominent enough, causing users to spend more time identifying the target.

The effect size of Group C and other groups on Fixation Count ranges from 0.630 to 0.703, which is a medium to large effect size. This shows that users in Group C need more fixations when looking for target information. This may be due to the unclear layout of interface information or insufficient visual cues of target symbols, which causes users to need more time and attention when looking for information.

The effect size of Group C and other groups on Revisits Count ranges from 0.479 to 0.953, which is a medium to large effect size. In particular, the effect size between Group C and Group B is close to 1 (0.953), showing a large difference. This shows that users in Group C need to frequently review the interface during use. This may be due to unclear information transmission or complex operation logic. Users cannot understand the interface information at one time and need to review and confirm it repeatedly.

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The effect sizes of Group C and other groups on Task Completion Time ranged from 0.027 to 0.851. Among them, the effect sizes of Group C and Group A and Group B are larger (0.461 and 0.851), indicating that users in Group C spend significantly more time completing tasks than other groups. This may reflect Group C's deficiencies in interface guidance and interaction fluency, which caused users to encounter difficulties during task execution, thus prolonging the Task Completion Time.

The effect sizes of Group C and other groups on Error Rate and Help Request Rate are both greater than 5 (Cohen's d = 6.541 and 5.332), which are extremely large effect sizes. This shows that there is a very significant difference between Group C and other groups on these two indicators, indicating that users in Group C make more mistakes when using the interface and need more help. Such a high effect size may reflect that Group C has obvious flaws in interface design, interaction process, information transmission, etc., causing users to encounter more problems during operation and frequently seek help.

Cohen's d effect size histogram shows the difference between group C and other groups on different indicators. It shows that the effect sizes of Error Rate and Help Request Rate are very high (greater than 5), indicating that group C is different from other groups on these indicators. There are very significant differences between the categories. The effect sizes of Fixation Count, Revisits Count, Fixation Duration and Task Completion Time range from 0.4 to 1, indicating that these indicators also have significant differences between group C and other groups, but not as much as Error Rate and Help Request Rate. Significantly.

Multivariate Analysis

Principal Component Analysis (PCA) was used to identify the underlying patterns between different groups, as shown in Figure 3.

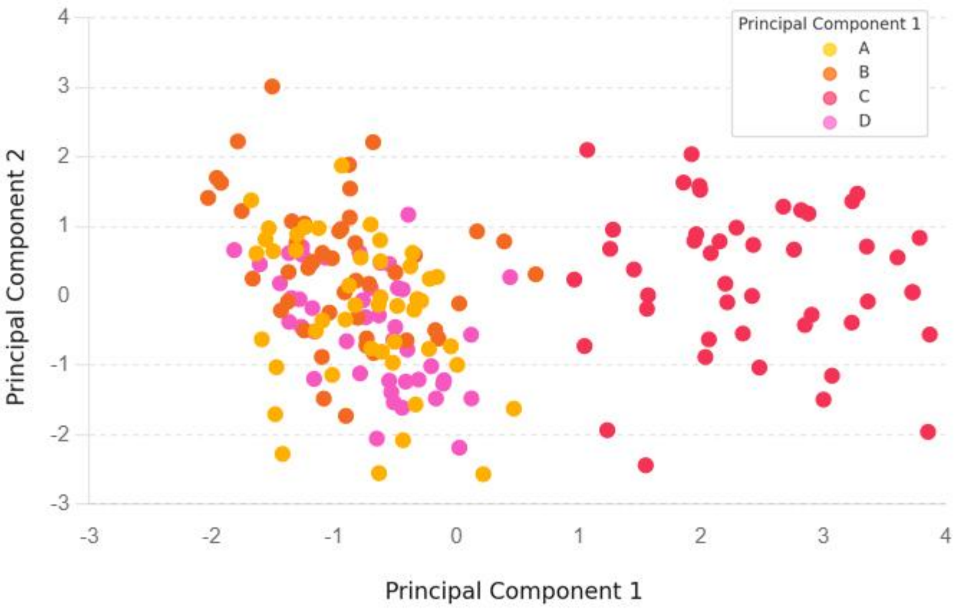

Figure 3: PCA of Different Groups

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The PCA results showed the distribution of the groups across the first two principal components. PC1 (Principal Component 1) explains 39.15% of the variance. PC2 (Principal Component 2) explains 17.93% of the variance. Together, the first two principal components explained 57.08% of the variance. The PCA plot showed a certain degree of separation between the groups in PC1 and PC2. Group C was distinctly separated from the other groups, indicating significantly different performance across multiple metrics. Group C exhibited behavior patterns that were distinct from those of the other groups. Groups A, B, and D were closer together in their distribution of PC1 and PC2, suggesting similar behavior patterns.

The analysis revealed significant differences between group C and the other groups across multiple metrics. The fixation count marginally affected the task completion time. PCA shows that ’s behavior patterns of group Care notably different from those of the other groups.

Usability Analysis
The usability analysis revealed significant differences among the four interface samples in terms of efficiency, effectiveness, and learnability. Sample A demonstrated the highest efficiency with the shortest fixation duration and task completion time, indicating clear visual cues and effective layout design. In contrast, Sample C exhibited the lowest efficiency, characterized by the longest fixation duration and highest fixation count, suggesting insufficiently intuitive visual elements and layout. In terms of effectiveness, Sample A and Sample B achieved the best results, with 0% error rates and minimal task completion times, reflecting their user-friendly and intuitive designs. Sample C, however, had the highest error rate, indicating unclear information presentation and operational complexity that significantly hindered task performance. Regarding learnability, Sample B outperformed the others with the fewest regression counts and no help requests, demonstrating smooth navigation and ease of use. Conversely, Sample C showed poor learnability, with the highest regression counts and help request rates, highlighting significant navigation and interaction challenges. Overall, while Samples A and B exhibited superior usability, Sample C required substantial design optimizations to address its usability issues and improve user interaction efficiency, accuracy, and satisfaction.

Table 6: Summary of Findings Across Samples A, B, C, and D

Metric	Sample A	Sample B	Sample C	Sample D	Key Insights
Fixation Duration	Shortest	Moderate	Longest	Moderate	Sample C shows significantly longer fixation durations, indicating difficulty in processing information.
Fixation Count	Moderate	Fewest	Most	Moderate	Sample C requires the most fixations, suggesting unclear layout or insufficient visual cues.
Regression Count	Moderate	Fewest	Most	Moderate	Sample C has the highest regression count, reflecting navigation difficulties and unclear design.

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Metric	Sample A	Sample B	Sample C	Sample D	Key Insights
Task Completion Time	Shortest	Moderate	Longest	Moderate	Sample C has the longest task completion time, indicating inefficiencies in interface guidance.
Error Rate	0	0	Highest	0	Sample C exhibits the highest error rate, while others show no errors, indicating interface flaws in C.
Help Request Rate	0	0	Highest	0	Sample C users needed the most help, suggesting significant usability issues compared to others.

Conclusion

This study aimed to evaluate the usability of cultural tourism smart guide map interfaces based on visual cognitive characteristics using eye-tracking technology. The main findings revealed significant differences in users' visual attention, efficiency, effectiveness, and learnability across the four interface samples studied. Specifically, the Travel to Jiayuguan (Sample C) exhibited the lowest usability performance, with longer fixation durations, higher fixation counts, more regressions, and a higher rate of errors and help requests. In contrast, the Nanjing Presidential Palace Guide (Sample B) and Wuzhen Cultural Tourism Smart Guide (Sample A) exhibited superior performance in these usability metrics, indicating their more user-friendly and intuitive designs.

The contributions of this research are twofold. First, it provides a scientific evaluation model for measuring the effectiveness of visual cognitive features in cultural tourism maps. Second, it offers actionable recommendations for the design of smarter and more user-friendly guide maps that can significantly improve the efficiency and satisfaction of users. These findings align with and expand the existing literature on the application of eye-tracking technology in interface usability evaluations, particularly in the context of cultural tourism smart guides. Consistent with prior studies, the results reaffirm that the interface layout, task complexity, and visual attention capacity significantly impact user interaction efficiency (Bai, Law, & Wen, 2021; Zhao, 2021). The data also emphasize the importance of designing interfaces that reduce the cognitive load by simplifying visual elements and optimizing information presentation (Joseph & Murugesh, 2020). In the context of smart tourism, these insights provide valuable guidance for practitioners aiming to improve the user experience by focusing on interface simplicity and intuitiveness.

This study contributes to the ongoing research by providing empirical evidence on how specific design elements, such as layout and information density, affect user performance. It also opens avenues for further investigation into how cultural elements in interface design might influence user behavior and engagement in cultural tourism contexts, suggesting that future research should explore the intersection of culture and usability to enhance the effectiveness of digital tools in tourism.

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This study, while offering valuable insights into the usability of cultural tourism smart guide map interfaces, has some limitations. The relatively small sample size and controlled laboratory settings may limit the generalizability of the findings, as real-world conditions and larger, more diverse participant groups could yield different results. Additionally, the study focused on four specific interfaces, potentially overlooking other innovative designs and broader cultural contexts. Future research should explore more diverse samples, naturalistic settings, and a wider range of interactive features. Long-term user engagement and satisfaction were also not addressed, which could be investigated in longitudinal studies to deepen understanding.

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