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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: Visual cognitive characteristics, Cultural tourism smart guide, Map interface, Interface evaluation, Visual attention

INTRODUCTION

Cultural tourism guide maps are vital tools for providing tourists with convenient route planning and attraction information. With the advancement of smart tourism, interactive sharing features have become an essential component of modern guide maps, directly influencing the user experience and satisfaction (Bai, Law, & Wen, 2021; Zhao, 2021). Eye Tracking technology can accurately record user visual behavior and attention distribution, thereby providing scientific basis for interface optimization (Diego-Mas et al., 2019; Rezae et al., 2020). This study aimed to evaluate the usability of interactive sharing features in cultural tourism guide maps using Eye Tracking technology. The specific objectives include collecting and analyzing Eye Tracking data from users while using guide maps and identifying and assessing the performance differences of interactive sharing features across different samples (Cybulski et al., 2023). By employing scientific experimental methods and data analysis, this study reveals usability issues in the interactive sharing features of cultural tourism guide maps, providing strong support for future design optimizations, thereby enhancing user experience and satisfaction, and promoting the development of smart tourism (Gretzel et al., 2020; Munjal, 2021).

LITERATURE REVIEW

Application of Eye Tracking Technology in Human-Computer Interaction

Eye Tracking technology records and analyzes user eye movements, providing rich data on user visual attention and behavior, and is widely applied in human-computer interaction research (Souza et al., 2022; Szekely et al., 2023). First, eye tracking technology helps optimize interface design by analyzing user fixation points and paths, identifying the most and least attention-grabbing parts of the interface, and adjusting the layout and information presentation to improve user experience and operational efficiency (Johnson, Smith, & Peterson, 2020; Joo & Jeong, 2020). In user experience evaluation, eye tracking technology records user eye tracking data and analyzes attention distribution, confusion points, and operational habits to provide a scientific basis for product design improvements (Scalera et al., 2021; Yang, 2022). For example, e-commerce websites help identify information that attracts user attention while purchasing decisions and optimizing product displays and recommendation systems (Wegner et al., 2020). Eye Tracking technology is also a crucial tool for usability testing, quantitatively assessing user efficiency and accuracy in completing specific tasks by analyzing eye tracking data (Kim et al., 2022). For instance, in software usability testing, it helps identify user difficulties and errors during operation, optimizing the interface design and functionality (Ismail et al., 2022). In education and training, eye tracking technology records students' eye movements during learning and analyzes attention distribution and comprehension to improve the teaching content and methods (Yang, Othman, & Hussin, 2024). Driving training evaluates driver attention and reaction speed, enhancing driving safety (Sweller, Ayres, & Kalyuga, 2021). In advertising and marketing, eye tracking technology evaluates ad attractiveness and effectiveness by analyzing consumer fixation points and times, understanding advertisement attractiveness and information transmission, optimizing ad design, and improving ad effectiveness (Matulewski et al., 2023). In medical and psychological research, eye tracking technology is crucial for diagnosing neurological and psychological disorders, such as autism and ADHD, by analyzing patients' eye movements (Yang, Su, & Shen, 2021; Sim & Bond, 2021). It has also been used to study visual cognition and behavioral patterns, providing new perspectives for psychological research (Ugwitz et al., 2022).

In summary, eye tracking technology is widely applied in human-computer interaction, providing detailed user visual behavior data to support interface design, user experience evaluation, usability testing, education and training, advertising and marketing, and medical and psychological research (Hassenzahl & Tractinsky, 2020).

Application of Eye Tracking Technology in Interface Usability Evaluation

Eye Tracking technology records and analyzes user eye movements to reveal visual behavior and attention distribution during interface use, providing a scientific basis for interface optimization (Zhang & Cui, 2022). First, it evaluates user attention and understanding of interface elements by analyzing fixation points and fixation duration, determining which elements attract user attention and which are ignored (Menzel et al., 2022). Second, it identifies user confusion points and operational difficulties during interface use by analyzing regression counts and fixation paths, discovering design issues, or unclear information (Joseph & Murugesh, 2020). Additionally, eye tracking technology evaluates interface learnability and operational efficiency by recording fixation count and fixation duration and analyzing user operational smoothness and information search efficiency (Yang & Su, 2021). A lower fixation count and shorter fixation duration indicate that users can quickly find the required information and complete tasks. For example, in mobile app usability evaluation, eye tracking technology helps identify common user issues and optimizes interface design. It can also be combined with surveys and interviews to provide comprehensive usability evaluation results, combining subjective feedback with objective eye tracking data for deeper insights into user experience and operational habits (Yang, Hussin, & Othman, 2024).

In summary, eye tracking technology is widely applied in interface usability evaluation, providing detailed user visual behavior data to support interface design optimization, user experience enhancement, and operational efficiency improvement (Szwarc et al., 2023).

Interface Usability Evaluation

The usability evaluation of the interface included several aspects. Efficiency measures the speed at which users complete tasks, as assessed by the fixation duration and fixation count (Diego-Mas et al., 2019). A shorter fixation duration and fewer fixation counts indicate that users can quickly find information and complete tasks. Effectiveness measures the accuracy and success rate of task completion, as assessed by the task completion time and error rate (Kim et al., 2022). A shorter completion time and lower error rate indicate an intuitive interface design. Learnability measures the difficulty of learning the interface for the first time, as assessed by the regression count and help request rate (Joseph & Murugesh, 2020). Fewer regressions and help requests indicated a user-friendly and easy-to-learn interface. Satisfaction measures subjective user satisfaction, obtained through surveys and interviews, to understand the overall user experience and feelings (Menzel et al., 2022). Error tolerance measures the interface's ability to handle user errors, with high-error-tolerance interfaces helping users correct mistakes and reduce negative impacts.

Evaluation methods include Eye Tracking, user testing, surveys, and expert evaluations. Eye Tracking records visual behavior, provides quantitative data, user testing observes operations to find usability issues, surveys collect subjective feedback, and expert evaluation involves systematic analysis by domain experts (Yang, Su, & Shen, 2021).

In summary, although the application of eye tracking technology in human-computer interaction and interface usability evaluation has been widely studied, existing research focuses more on general fields such as e-commerce, advertising, and medical care (Rezae et al., 2020). However, relatively few visual behavior data analyses have been conducted at the interface of cultural tourism smart guide maps. Especially in the context of cultural tourism, the effect of complex interface designs involving cultural elements on users' visual cognition and operational efficiency has not been deeply explored. In addition, existing studies mostly emphasize single interface design features while ignoring the comprehensive impact of interactivity and cultural background on user experience. Therefore, this study fills the gap in visual behavior analysis at the interface of cultural tourism smart guide maps in this field and explores how the combination of culture and technology affects users' cognition and behavior (Gretzel et al., 2020; Munjal, 2021).

METHODOLOGY

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.

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.

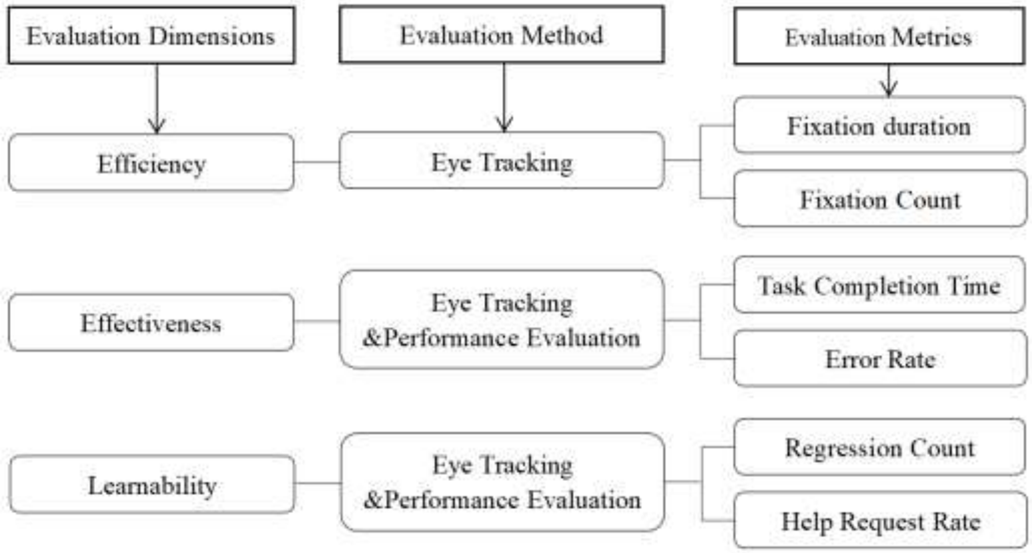

Figure 1. Usability Evaluation Model.

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 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).

FINDINGS AND 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 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.

Table3. 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		

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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, 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

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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.

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

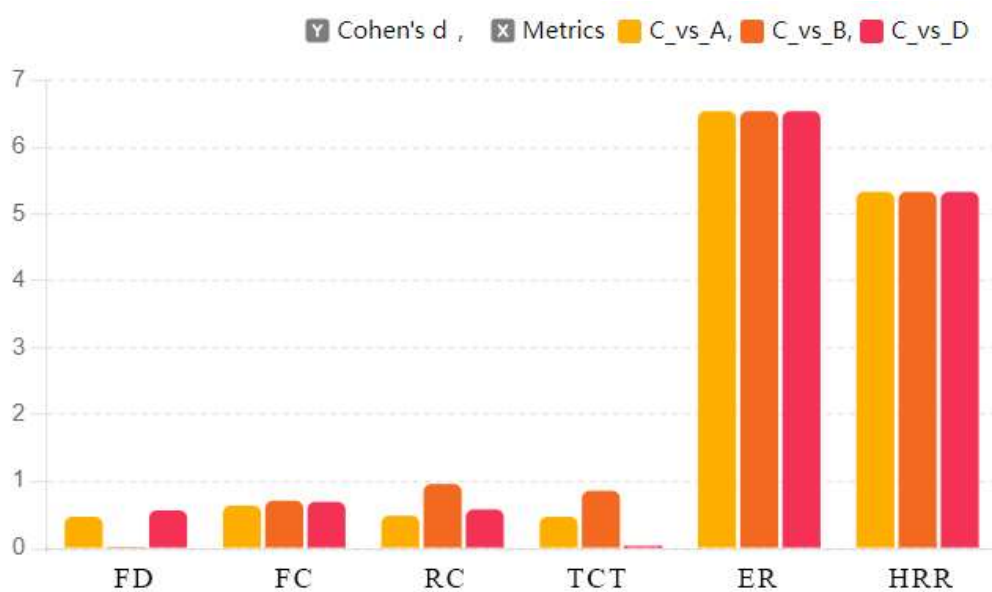

Figure 2. Cohen's D effect sizes by metric.

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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.

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

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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.

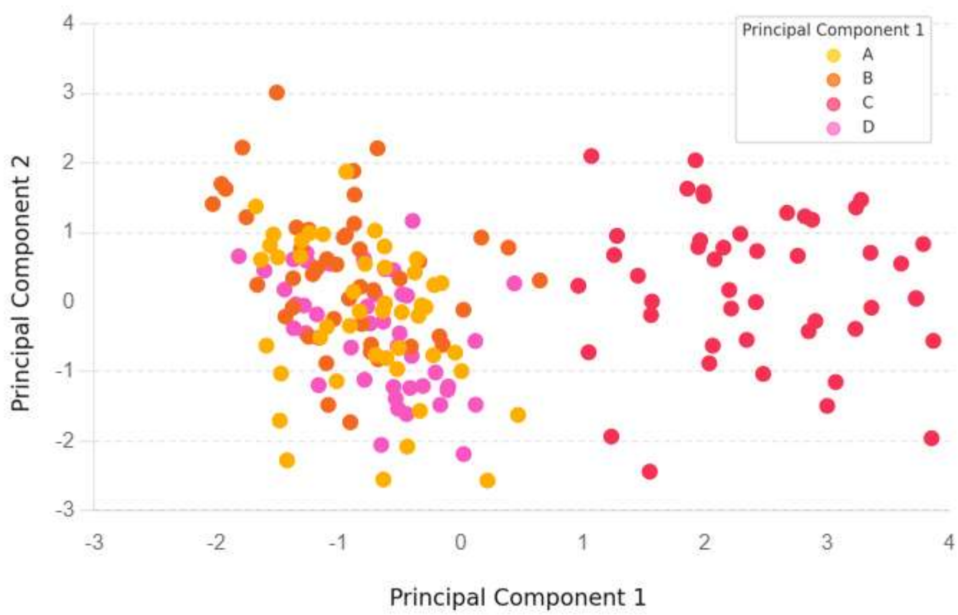

Figure 3. PCA of Different Groups.

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

Based on the comprehensive analysis results, the following usability analysis was conducted for each metric: Efficiency-Fixation Duration: Sample A had the shortest fixation duration, indicating the highest visual search efficiency, while Sample C had the longest fixation duration, indicating the lowest efficiency.Fixation Count: Sample B has the fewest fixations, indicating the highest information search efficiency; Sample C has the most fixations, indicating the lowest efficiency. Effectiveness-Task Completion Time: Sample A had the shortest task completion time, indicating the highest effectiveness in completing tasks. Sample C had the longest task completion time, indicating the lowest effectiveness.Error Rate: Sample C has a significantly higher error rate than the other groups, indicating lower effectiveness; Samples A, B, and D have an error rate of 0, indicating high effectiveness. Learnability-Regression Count: Sample B has the fewest regressions, indicating easier target location and effective interface design; Sample C has the most regressions, indicating lower learnability. Help Request Rate: Sample C has the highest help request rate, indicating that users need more help during usage, indicating lower learnability. Samples A, B, and D have a help request rate of 0, indicating high learnability. Considering efficiency, effectiveness, and learnability comprehensively, Sample B performs the best in the usability evaluation of the sharing feature, whereas Sample C needs further design optimization.

IMPLICATION TO RESEARCH AND PRACTICE

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.

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.

FUTURE RESEARCH

However, this study had some limitations. The relatively small sample size and controlled laboratory settings may not fully reflect the real-world conditions. Future studies should involve larger and more diverse participant groups and explore different environmental conditions to generalize the findings. Moreover, future research should focus on evaluating a wider range of interactive features in diverse cultural contexts to enhance the universality and applicability of the results. Research should explore a wider range of guide map types and different interactive sharing feature designs to comprehensively evaluate their usability and user experience.

CONFLICTS OF INTEREST

The author asserts that there are no conflicts of interest concerning the publication of this article.

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