

Evaluating the Usability of Interactive Disease Data Visualization Using the System Usability Scale

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Abstract:

This study evaluates the usability of a municipal disease data visualization system through the lens of interaction design, using the System Usability Scale (SUS) as the core assessment framework. A structured questionnaire was administered to 320 medical faculty and students, capturing user perceptions across three key dimensions: perceived task complexity, information density, and information salience. The study extends the standard SUS by incorporating custom hypothesis-driven items related to task flow, interaction behavior, and visual design elements. Results indicate that all three design factors exert significant influence on user experience, with regression models demonstrating high predictive power. Streamlined task flows were found to reduce cognitive load, intuitive interaction behaviors improved recognition of information structure, and optimized visual design enhanced the salience of key data points. The findings validate the applicability of SUS in evaluating complex medical visualization systems and offer a methodological reference for integrating user-centered quantitative analysis into interface design. Future research directions include hybrid evaluation approaches combining SUS with behavioral data such as eye-tracking or click heatmaps.

Keywords:

Usability Evaluation, Interaction Design, System Usability Scale, Data Visualization

1. Introduction

With the ongoing advancement of big data and artificial intelligence technologies, the field of public health and healthcare has witnessed the widespread adoption of data visualization. In the face of massive, multi-sourced, and heterogeneous health data, the challenge of how to enhance users' information perception and decision-making capabilities through effective visual interfaces has become a central concern in both design research and practical applications. Particularly in the context of disease data presentation, users are required not only to comprehend complex data structures but also to perform interactive tasks efficiently—placing interactive design at the core of the human–computer information transmission process.

In recent years, an increasing number of disease surveillance and epidemiological systems have adopted data visualization to replace traditional tabular reports, aiming to make information more perceptible, traceable, and analyzable. However, existing research tends to focus on technical performance, data accuracy, or visual representation, while often neglecting systematic evaluations of users' experience and interaction effectiveness. This gap significantly hampers the practical deployment of visualization tools and reduces user retention. In complex multidimensional interfaces—characterized by dense graphics, hierarchical layering, and high information density—ignoring usability assessment can easily result in user confusion, task failure, or cognitive overload.

Usability, defined as a system's ease of learning, efficiency of use, memorability, error frequency, and user satisfaction, has long been a cornerstone of human–computer interaction (HCI) and interface design research. The demand for quantifiable usability evaluation is particularly pressing when systems are deployed among heterogeneous user groups, such as medical professionals and public health students. The System Usability Scale (SUS), as a rapid, low-cost, and highly reliable evaluation instrument, has demonstrated strong versatility and cross-system applicability in capturing users' subjective perceptions of overall system ease of use.

This study evaluates the usability of a disease data visualization system in a Chinese city through the lens of the SUS questionnaire, focusing specifically on its interaction design. From the user's perspective, the study aims to capture key experiential indicators such as satisfaction, ease of use, and logical consistency during system operation. By collecting feedback from medical school users and applying statistical analysis techniques, this research reveals the system's performance in areas such as operational efficiency, interface friendliness, and learning curve adaptability. The findings not only fill an empirical gap in the usability evaluation of localized disease data visualization systems, but also offer a paradigm for integrating user-centered quantitative assessment methods into future system design processes.

2. Literature Review

Usability, as a core concept in interaction design research, refers to users' performance and perceptions in terms of learnability, task efficiency, error frequency, memorability, and overall satisfaction when operating a system or interface. Nielsen [3] proposed a five-dimensional model—learnability, efficiency, memorability, low error rate, and satisfaction—which has since become a widely accepted framework in usability evaluation, particularly in applications such as health information dashboards, mobile visualizations, and interactive data platforms [5].

In the context of disease data visualization, designers must balance medical specificity, data complexity, and interface usability. Multidimensional visual structures, densely packed graphics, and nonlinear navigation often impose high cognitive loads, impeding users' ability to comprehend information and complete tasks effectively [8]. Rind et al. [7] emphasized the importance of visual hierarchy and streamlined interaction logic in enhancing users' perception of patterns such as trends, anomalies, and causality during analytical tasks.

The SUS developed by Brooke [2], is a widely adopted, low-cost usability assessment tool that employs a 10-item Likert-scale questionnaire to evaluate users' subjective perceptions of system usability [2]. Its advantages lie in simplicity, reliability, and broad applicability across platforms—including websites, health apps,

dashboards, and visualization interfaces [1]. SUS scores can be interpreted using acceptability thresholds (e.g., scores above 70 indicating good usability), or converted to A–F grades and percentile curves to facilitate diagnostic insights [4].

In recent years, the SUS has been increasingly used in evaluating health information visualization systems. Perkhofer and Lehner [9], for example, integrated SUS with eye-tracking data and found a strong correlation between users' subjective satisfaction and visual attention patterns in cognitively demanding interfaces. In another empirical study, Li, Wang, and Hu [11] demonstrated that while 3D visualizations offer aesthetic appeal, 2D Cartesian interfaces outperform them in terms of task efficiency and readability—reflected clearly in their respective SUS scores.

However, despite its growing adoption, the systematic application of SUS in disease data visualization remains limited. While some scholars in China have applied SUS in evaluating mobile health apps [6] or electronic health records, there is a noticeable gap in using SUS to assess region-specific public health platforms that integrate complex multidimensional big data interfaces. Furthermore, existing SUS-based evaluations often focus solely on user interfaces, without accounting for contextual factors such as local health literacy or visual complexity [8]. This highlights a need for more integrative studies that bridge theoretical constructs with real-world design contexts.

3. Methodology

This study aims to evaluate the usability of an interactive disease data visualization system in a specific region using the SUS. To ensure both the representativeness and practical relevance of the assessment results, the methodology combines real-world interaction tasks, targeted user groups, and standardized survey tools. The research design includes experimental task development, participant selection, SUS questionnaire administration, and statistical analysis.

3.1. Research Participants and Experimental Tasks

To ensure that the experimental findings accurately reflect the characteristics of the system's actual user base, the study recruited faculty and students from a medical school at a university as the primary participants. This group regularly engages with medical data and possesses both a fundamental medical background and basic computer literacy, enabling them to provide valid evaluations of the system's interaction design from a professional perspective. Considering variations in user age, cognitive capacity, and information processing habits, participants were required to be between 18 and 60 years old and to have normal or corrected-to-normal vision, in order to eliminate non-design-related biases.

To ensure the scientific validity and representativeness of the sample, the study employed stratified random sampling based on occupation (faculty/student) and age groups. Referring to the Morgan Sample Size Table, the final sample size was set at 320 participants. As shown in Table 1, the sample included a representative subset of 120 faculty members and 1800 students, stratified by different age groups and occupational backgrounds, thus providing a sound empirical foundation for usability analysis of the interaction design.

Table 1. Questionnaire Survey Sampling Method and Sample Size.

Stratified categories	Subgroup	Total population	Sample size	Explanation	Sampling method
Professional background	Teacher	120	20	Including teachers of different age groups	Random sampling
	Student	1800	300	Including students of different age groups	
Teacher age group	Teacher: ≤ 35 years old	30	5	Ensuring representation of young teachers	
	Teacher: 36-50 years old	60	10	Main age group, relatively larger sample size	
	Teacher: >50 years old	30	5	Ensuring representation of older teachers	
Student age group	Student: ≤ 20 years old	600	100	Ensuring representation of young students	
	Student: 21-30 years old	1200	200	Main age group, relatively larger sample size	

To evaluate the usability of the system’s interaction design, the study developed experimental tasks based on typical usage scenarios, including data retrieval, chart interpretation, information comparison, and interactive operations. These tasks simulated the real-life use of the system in professional settings, such as browsing disease data, filtering patient cases, and interpreting visualized graphics. The goal was to assess users’ intuitive understanding and operational efficiency across various dimensions, such as task flow, interaction feedback, and visual presentation, as illustrated in Figure 1.

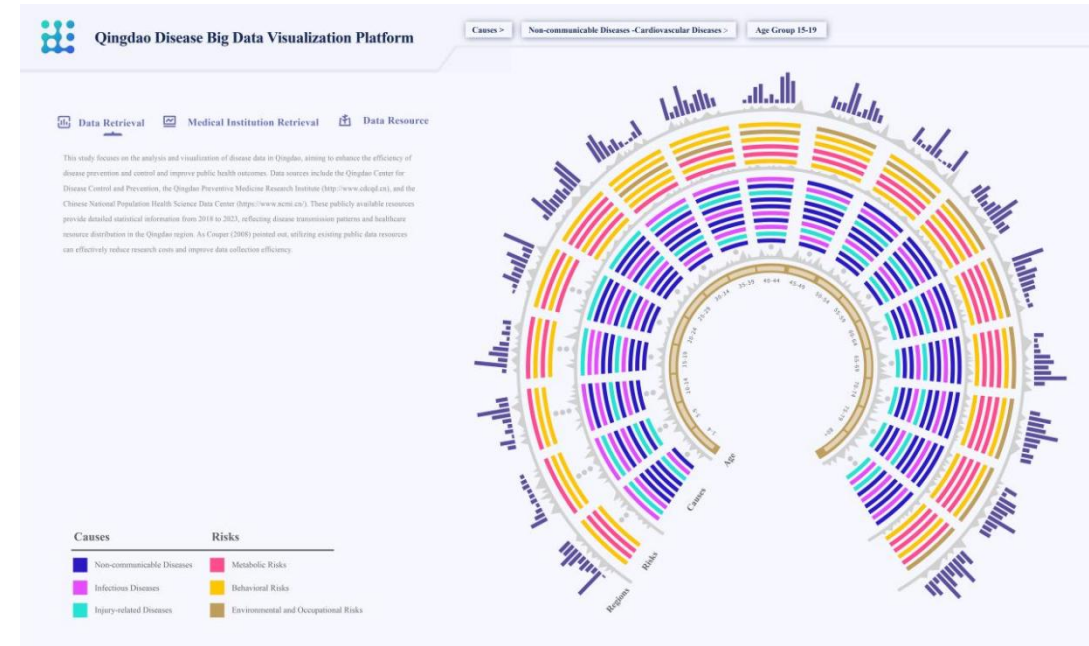


Figure 1. A Municipal Disease Big Data Visualization Platform.

All experimental tasks were completed through the online system interface. Participants were instructed to perform specific operations within a limited timeframe

and subsequently complete a SUS-based evaluation questionnaire. This questionnaire quantified their user experience across three dimensions: perceived complexity, information density, and visual saliency. The task design emphasized “real-world task orientation” to ensure the ecological validity of user feedback and to provide actionable evidence for interaction design optimization.

3.2. SUS Questionnaire Design and Implementation

This study employed the SUS as the core evaluation instrument to assess the usability performance of a disease data visualization system from an interaction design perspective. Originally proposed by John Brooke in 1986, the SUS is a widely adopted, easy-to-administer, and highly reliable usability measurement tool. It has been applied across a range of domains, including industrial systems, commercial software, and web platforms. The questionnaire consists of 10 items rated on a 5-point Likert scale, alternating between positive and negative statements to reduce response bias. It evaluates user experience across multiple dimensions, such as operational ease, task completion fluency, interface complexity, and functional integration.

Given that this study focuses on the influence of specific interaction design factors on user perception, the standard SUS questionnaire was extended through customized design. A set of structured items was developed, oriented around three core hypotheses. Each hypothesis consists of three independent variable items and one dependent variable item, corresponding to the relationships between “task flow and perceived complexity,” “interaction behavior and information density,” and “visual design elements and information saliency.” This extended format enhances the interpretability of the questionnaire in the context-specific evaluation. Table 2 presents the detailed mapping between the hypotheses and questionnaire items.

Table 2. Customized Questionnaire and Correspondence with Hypotheses.

Serial Number	Question Content	Corresponding Hypothesis	Variable Type
5	I think the system's task flow is very clear and straightforward.	Hypothesis 1: Establishing user tasks can significantly reduce the complexity perceived by users.	IV: User Task Flow
6	I can easily complete operations such as searching and filtering data.		
7	The system's task design matches my expectations and usage habits.		
8	I think the system's task flow reduces the complexity of using the system.		DV: Complexity
9	I think the system's interaction design is intuitive.	Hypothesis 2: Appropriate interactive behaviors can significantly optimize information density.	IV: Interactive Behavior
10	I believe the interactive behaviors in the system allow for quick information retrieval.		
11	I think the system's interaction feedback makes it easy for me to identify information.		
12	I believe the amount and presentation of information provided by the system are appropriate.		DV: Information Density
13	I believe the system's visual layout makes important information easy to recognize.	Hypothesis 3: Good adjustment of visual elements can significantly enhance the salience of information.	IV: Visual Design Elements
14	I think the system's color scheme makes the information stand out.		
15	I believe the system's font size and style make important information easy to identify.		

16	I think the visual changes in the system effectively highlight information.		DV: Information Saliency
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The questionnaire was distributed online via the Wenjuanxing platform (wjx.cn), incorporating logic branching and mobile-responsive optimization to ensure cross-device compatibility and a smooth user experience. All questions were mandatory, supplemented with example items and detailed instructions to improve data completeness and response accuracy. Additionally, range validation and format checking mechanisms were implemented to control outliers and logical inconsistencies, thereby improving the structural integrity and analytical validity of the collected data.

Upon completion of the survey, responses were exported automatically and processed using SPSS. Prior to analysis, all records were anonymized to remove personally identifiable information, ensuring participant privacy. The data collection and storage procedures strictly adhered to ethical guidelines and information protection standards within academic research. Through this comprehensive questionnaire design and implementation process, the study ensured the applicability of the SUS instrument, the reliability and validity of measurement, and the quality of data collection—laying a solid foundation for hypothesis testing and further optimization of interaction design.

3.3. Data Analysis Method

This study employed the SUS as the primary evaluation tool to quantitatively assess the usability of a disease data visualization interface from an interaction design perspective. The SUS comprises 10 items, with scores calculated using a standardized reverse-scoring method. The total raw score is multiplied by 2.5 to convert it to a 0–100 scale. This standardized score provides an intuitive reflection of users' perceived system usability and supports both cross-sectional comparison and longitudinal performance monitoring. In addition, key descriptive statistics such as the mean and standard deviation were calculated to capture overall user satisfaction and rating consistency, offering insight into the system's usability performance.

Beyond the overall SUS score, the study extended the questionnaire design based on three core research hypotheses, enabling a more granular analysis of how specific design dimensions—task flow, interaction behavior, and visual saliency—affect user perception. For each dimension, three independent variable items and one dependent variable item were developed, corresponding to perceived task complexity, information density, and saliency, respectively. Accordingly, the data analysis process involved not only computing basic statistical indicators of the SUS score distribution, but also applying a range of inferential statistical methods for deeper analysis. These included reliability testing (Cronbach's alpha), construct validity analysis (KMO and Bartlett's tests), correlation analysis (Pearson's r), and regression modeling, thereby providing a comprehensive evaluation framework for usability diagnosis and design optimization.

4. Results

4.1. The Impact of Task Flow Design on Perceived Task Complexity

To investigate how user task design affects perceived complexity in interactive systems, this study first conducted reliability and validity tests, followed by correlation and regression analyses. The reliability analysis revealed a high level of

internal consistency, with the Cronbach's alpha coefficient for the task flow scale reaching 0.865. When individual items were removed, the alpha values remained between 0.762 and 0.857, indicating stable contributions of all items and a well-structured scale (see Table 3). In terms of construct validity, the Kaiser–Meyer–Olkin (KMO) measure was 0.718, and Bartlett's test of sphericity was statistically significant ($\chi^2 = 459.815$, $df = 3$, $p < .001$), confirming the suitability of the data for factor analysis (see Table 4).

Table 3. Questionnaire Reliability Analysis Table 1.

Reliability Statistics			
Item	Number of Items	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
1-1.I think the system's task flow is very clear and straightforward.	3	0.807	0.865
1-2. I can easily complete operations such as searching and filtering data.		0.857	
1-3.The system's task design matches my expectations and usage habits.		0.762	

Table 4. Questionnaire Validity Analysis Table 1.

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy		0.718
Bartlett's Test of Sphericity	Approximate Chi-Square	459.815
	df	3
	Significance	0.000

Correlation analysis further validated the linear relationship between task flow and perceived complexity. The Pearson correlation coefficient was 0.820 ($p < .001$), suggesting a strong positive correlation between the two variables (see Table 5). This result indicates that the more streamlined and clearly structured the task flow, the lower the cognitive load perceived by users during operation.

Regression analysis provided additional support for this conclusion (see Table 6). The regression model showed an R^2 of 0.673 and an adjusted R^2 of 0.672, suggesting that task flow design accounted for 67.2% of the variance in users' perceived complexity. The standardized regression coefficient (Beta) was 0.820, and the model was statistically significant ($F=636.590$, $p < .001$), with no multicollinearity issues ($VIF= 1.000$). These findings confirm Hypothesis 1 and underscore the critical role of effective task flow design in enhancing usability and reducing users' cognitive burden.

Table 5. Variable Correlation Analysis Table 1.

Correlation				
	N	Mean	Perceived Complexity by Users	Establish User Tasks
Perceived Complexity by Users	311	3.57	1	0.820**
Establish User Tasks	311	3.47	0.820**	1
**. Correlation is significant at the 0.01 level (2-tailed).				

Table 6. Regression Model Summary Table 1.

Model Summary									
Model	R	R^2	Adjusted R^2	Standard Error of the Estimate	Change Statistics				
					R^2 Change	F Change	df 1	df 2	Significance of F Change
1	0.820a	0.673	0.672	0.746	0.673	636.590	1	309	0.000
a. Predictors: (Constant), X1									

4.2. The Impact of Interaction Behavior on Perceived Information Density

This section further examines the influence of interaction behavior on users' perception of information density, evaluating the design from three key aspects: intuitiveness, operational efficiency, and clarity of feedback. The reliability analysis yielded a Cronbach's alpha value of 0.855, indicating good internal consistency. When individual items were removed, the alpha values remained between 0.790 and 0.807, demonstrating the structural soundness of the scale (see Table 7). The construct validity was also supported, with a KMO value of 0.734 and a significant result from Bartlett's test of sphericity ($\chi^2 = 410.572$, $df = 3$, $p < .001$), confirming the data's suitability for factor analysis (see Table 8).

Table 7. Questionnaire Reliability Analysis Table 2.

Reliability Statistics			
Item	Number of Items	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
2-1.I think the system's interaction design is intuitive.	3	0.807	0.855
2-2.I believe the interactive behaviors in the system allow for quick information retrieval.		0.793	
2-3.I think the system's interaction feedback makes it easy for me to identify information.		0.79	

Table 8. Questionnaire Validity Analysis Table 2.

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy		0.734
Bartlett's Test of Sphericity	Approximate Chi-Square	410.572
	df	3
	Significance	0.000

Correlation analysis revealed a strong positive relationship between interaction behavior and perceived information density, with a Pearson correlation coefficient of 0.776 ($p < .001$) (see Table 9). This finding suggests that smoother and more intuitive interaction feedback contributes to higher user recognition of a rational and well-structured interface. In other words, quality interaction design aligns closely with users' cognitive perception of information layout.

Regression analysis further reinforced this conclusion. The model yielded an R^2 of 0.603 and an adjusted R^2 of 0.601, indicating that interaction behavior explains 60.3% of the variance in perceived information density (see Table 10). The standardized regression coefficient (Beta) was 0.776, with a t-value of 21.649 ($p < .001$), demonstrating high statistical significance. Moreover, the Variance Inflation Factor (VIF) was 1.000, ruling out multicollinearity issues. These results confirm Hypothesis 2 and underscore the fundamental role of responsive interaction mechanisms in the design of complex data visualization interfaces.

Table 9. Variable Correlation Analysis Table 2.

Correlation				
	N	Mean	Optimize Information Density	Appropriate Interaction Behavior
Optimize Information Density	311	3.50	1	0.776**
Appropriate Interaction Behavior	311	3.33	0.776**	1
**. Correlation is significant at the 0.01 level (2-tailed).				

Table 10. Regression Model Summary Table 2.

Model Summary									
Model	R	R ²	Adjusted R ²	Standard Error of the Estimate	Change Statistics				
					R ² Change	F Change	df 1	df 2	Significance of F Change
1	0.776a	0.603	0.601	0.733	0.603	468.700	1	309	0.000
a. Predictors: (Constant), X2									

4.3. The Impact of Visual Design Elements on Perceived Information Salience

Visual design plays a critical role in guiding user attention and enhancing the efficiency of information recognition. This study focused on three key aspects—visual layout, color contrast, and typography norms—to assess their influence on the perceived salience of information. The reliability analysis showed exceptionally high internal consistency, with a Cronbach's alpha coefficient of 0.966. When individual items were removed, alpha values remained between 0.945 and 0.953, indicating excellent construct reliability (see Table 11). The Kaiser–Meyer–Olkin (KMO) value was 0.783, and Bartlett's test of sphericity was significant ($\chi^2 = 1131.874$, $df = 3$, $p < .001$), confirming strong structural validity for factor analysis (see Table 12).

Table 11. Questionnaire Reliability Analysis Table 3.

Reliability Statistics			
Item	Number of Items	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
3-1.I believe the system's visual layout makes important information easy to recognize.	3	0.951	0.966
3-2.I think the system's color scheme makes the information stand out.		0.945	
3-3.I believe the system's font size and style make important information easy to identify.		0.953	

Table 12. Questionnaire Validity Analysis Table 3.

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy		0.783
Bartlett's Test of Sphericity	Approximate Chi-Square	1131.874
	df	3
	Significance	0.000

Correlation analysis revealed a statistically significant positive relationship between visual design elements and perceived information salience, with a Pearson correlation coefficient of 0.748 ($p < .001$) (see Table 13). This indicates that optimized visual strategies—such as clear layout, strong color contrast, and legible fonts—effectively enhance users' ability to identify and focus on critical information within the interface.

Regression results further support this conclusion. The model demonstrated an R²value of 0.560 and an adjusted R²of 0.558, suggesting that visual elements accounted for 56.0% of the variance in perceived salience (see Table 14). The standardized regression coefficient (Beta) was 0.748, and the model was statistically significant ($F = 392.943$, $p < .001$). This means that for every one-unit improvement in visual design quality, user perception of information salience increases by 0.748 units. These findings confirm Hypothesis 3 and highlight the central role of visual optimization in the design of disease data visualization systems, particularly for supporting rapid and accurate information processing.

Table 13. Variable Correlation Analysis Table 3.

Correlation				
	N	Mean	Information Saliency	Good Visual Elements
Information Saliency	311	2.80	1	0.748**
Good Visual Elements	311	2.57	0.748**	1
**. Correlation is significant at the 0.01 level (2-tailed).				

Table 14. Regression Model Summary Table 3.

Model Summary									
Model	R	R ²	Adjusted R ²	Standard Error of the Estimate	Change Statistics				
					R ² Change	F Change	df 1	df 2	Significance of F Change
1	0.748a	0.560	0.558	0.867	0.560	392.943	1	309	0.000
a. Predictors: (Constant), X3									

5. Conclusions

This study conducted a systematic usability evaluation of a disease data visualization system's interactive design using the SUS. Based on structured questionnaire responses from a sample of 320 medical faculty and students, the quantitative analysis revealed that task flow design, interactive behaviors, and visual elements significantly influenced core usability dimensions—namely perceived complexity, information density, and information salience. Regression models confirmed that all three design factors demonstrated strong predictive power and statistical significance, thereby validating the applicability and explanatory power of SUS in evaluating complex medical information systems.

Specifically, streamlined and well-structured task flows significantly reduced users' perceived cognitive load during interaction, enabling more efficient retrieval and comparison of disease-related data. Intuitive interaction behaviors—particularly effective feedback mechanisms and information navigation paths—substantially improved users' perception of information density, enhancing both the accessibility and logical organization of the interface. On the visual front, thoughtful design of color schemes, layout hierarchy, and typography markedly increased the salience of key data points, helping users to rapidly locate critical information within visually dense interfaces. These three factors collectively form the foundational pillars for improving usability and underscore the central role of interaction design in disease data visualization systems.

Furthermore, the study demonstrated that SUS, as a low-cost and efficient evaluation instrument, is both applicable and scalable in the context of public health data visualization. Beyond capturing users' overall impressions of system usability, the SUS framework—when customized—can enable quantitative assessment of specific interaction factors, thus offering actionable insights for interface optimization. Future research may build upon this work by integrating multimodal user behavior data, such as eye-tracking and click heatmaps, with SUS-based subjective ratings. This hybrid evaluation strategy could enhance the comprehensiveness and precision of usability assessment, contributing both theoretical foundations and practical paradigms for the human-centered design of complex visualization systems.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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