
A Comprehensive Model for Evaluating Website Competence Using Web Mining Techniques

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Abstract

Evaluating websites has become increasingly critical as they function as primary platforms for information dissemination, communication, and digital service delivery. Website quality directly affects user experience and significantly influences the perceived credibility of online content. Although numerous evaluation models have been proposed, many remain constrained by manual assessment procedures, limiting their scalability and suitability for dynamic web environments.

To address these limitations, this study proposes a web-mining–driven evaluation model for assessing website competence through automated data extraction and weighted criteria analysis. The model integrates quantifiable indicators encompassing usability, content relevance, accessibility, reliability, and overall performance across multiple domains. Model robustness was validated through expert review and user-based evaluation. Statistical analysis demonstrates strong internal consistency (Cronbach’s alpha = 0.88), while content validity of the survey instrument—confirmed through expert evaluation—reached 0.94. Experimental results further indicate that the proposed approach outperforms existing methods, achieving 95% classification accuracy, high scalability, and an 80% user satisfaction rate, particularly in real-time evaluation contexts.

Overall, the proposed framework offers a transparent, evidence-based mechanism for website quality assessment. By minimizing subjectivity and enabling automated analysis, it enhances digital trust and supports informed decision-making for developers, policymakers, and end users across diverse application domains.

Keywords: Website Evaluation, Web Mining, Usability, Reliability, Criteria Assessment, Digital Platforms.

1. Introduction

The growing dependence on websites for commercial transactions, communication, and information exchange has intensified the need for reliable evaluation mechanisms capable of assessing their overall competence. Conventional assessment approaches typically depend on subjective human judgment and often lack the methodological depth required to address emerging concerns, including misinformation, accessibility barriers, and rapid changes in online content. To overcome these shortcomings, the present study proposes a structured evaluation model grounded in advanced web mining techniques and weighted assessment criteria. This structure enables automated, scalable, and objective evaluations that are adaptable across different website categories and domains.

Problem Statement:

Despite the proliferation of website evaluation frameworks, most existing models remain limited in their ability to provide automated, scalable, and objective assessments suitable for dynamic online environments. Many approaches rely heavily on manual or subjective evaluation methods, which introduce evaluator bias and reduce consistency across assessment contexts. Furthermore, current models often focus on domain-specific websites and fail to accommodate real-time changes in content, usability, accessibility, and reliability. This gap highlights the need for an integrated evaluation model that leverages web mining techniques to assess website competence in a systematic, objective, and scalable manner across diverse domains.

Research Hypotheses:

Based on the identified research problem, the study tests the following hypotheses:

- **H1:** The proposed web-mining-based evaluation model achieves higher accuracy in assessing website competence compared to traditional manual evaluation frameworks.
- **H2:** The integration of automated web mining techniques significantly enhances the objectivity and scalability of website evaluation.
- **H3:** The weighted criteria structure of the proposed model effectively differentiates between websites with varying levels of competence.
- **H4:** There is a statistically significant improvement in evaluation reliability when expert validation is incorporated into the model development process.

Scope and Limitations of the Study:

This study is subject to several limitations. First, the evaluation model was applied to a selected set of websites representing specific domains, and the findings may not fully generalize to all types of websites, particularly those with highly specialized or proprietary content. Second, the automated web mining techniques employed depend on the availability and accessibility of website data; therefore, dynamically generated or restricted content may not be fully captured. Third, the evaluation focuses on observable and measurable indicators, which may not entirely reflect subjective user perceptions such as aesthetic preference or emotional engagement. Finally, the study relies on current web mining tools and algorithms, and future technological advancements may further enhance model performance.

Operational Definitions:

- **Website Competence:** The overall ability of a website to deliver reliable, relevant, accessible, and high-quality information and services, as assessed through a set of weighted evaluation criteria.
 - **Web Mining:** The application of data mining techniques to extract, analyze, and interpret information from web content, structure, and usage data.
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- **Evaluation Criteria:** A predefined set of measurable indicators used to assess various aspects of website quality, including usability, content relevance, accessibility, reliability, and performance.
- **Automated Evaluation:** The process of assessing website quality using algorithmic and computational techniques without direct human intervention.
- **Weighted Criteria System:** A scoring mechanism in which evaluation criteria are assigned relative importance based on empirical user data and expert validation.

A review of the current literature reveals multiple directions in which website evaluation has been approached. One line of research focuses on content-based and algorithmic techniques, such as link analysis, sentiment analysis, and association rule mining, which have been applied to assess relevance and user engagement, with studies such as (Gao, 2019) emphasizing the importance of semantic accuracy. Another direction concern's reliability and quality assessment, particularly in academic and medical contexts, where usability, content accuracy, and privacy policies play core roles, as reflected in the work of (Battineni, Pallotta, Nittari, & Chintalapudi, 2021). Accessibility and usability studies have also gained attention, especially with respect to e-government and e-commerce platforms, where responsive design and intuitive navigation are highlighted as key determinants of user satisfaction (Verkijika & De Wet, 2018). Additionally, researchers have explored personalized web mining and recommender systems, aiming to enhance user experience through techniques such as fuzzy clustering and sentiment analysis (Chen, et al., 2020). Further contributions include the adoption of decision support systems like Data Envelopment Analysis (DEA) to evaluate resource efficiency and performance (Najadat, Al-Badarneh, & Alodibat, 2021), and interdisciplinary methodological frameworks combining perspectives from computing, business, and healthcare to develop broader evaluation perspectives (Morales Vargas & Pedraza-Jimenez, 2023). Although these studies provide valuable insights, several critical limitations remain unresolved. First, many frameworks are constrained in scalability, as they are tailored

to specific sectors and therefore lack the flexibility to assess general-purpose websites. Second, numerous models rely on subjective or manual evaluations, such as the CRAAP or SCARAP methods, which introduce inconsistency and potential evaluator bias. Third, most existing approaches do not support real-time assessment, focusing instead on static or historical website information, which is insufficient in today's fast-evolving digital environment.

The present research contributes to addressing these challenges through five main developments.

1. **A new website competence evaluation model** has been introduced, incorporating web mining to automate data collection and evaluation.
2. **A weighted criteria system** is established to assess credibility, transparency, content quality, timeliness, usability, and accessibility while ensuring fairness in scoring.
3. **Web mining techniques** are integrated to support automated extraction and real-time analysis of relevant website features.
4. The model responds to **contemporary digital concerns**, including misinformation and privacy, by incorporating fact-based evaluation and ethical safeguards.
5. It **provides practical value for various sectors**, enabling better-informed decisions by developers, policymakers, and users.

This work has direct relevance for a wide range of stakeholders. Web developers may use the model to diagnose performance and design issues. Content regulators and policymakers can benefit from its capacity to promote transparency and information integrity. End-users gain from clearer, more trustworthy online information ecosystems. Through a systematic review of the literature and empirical validation, the study not only identifies the shortcomings of previous evaluation models but also demonstrates the effectiveness of the proposed solution in real-world applications. The findings contribute to the fields of web mining, information retrieval, and decision

support systems and open avenues for continued progress in automated website evaluation.

The Related Work overview establishes that combining web mining with a weighted criteria structure presents a promising direction for addressing current evaluation limitations. To further illustrate this point, Table (1) compares the proposed framework with widely known website evaluation models and highlights the need for a more comprehensive, automated, and scalable approach.

Table (1): "Comparative Analysis of Website Evaluation Models and Frameworks"

Model/Framework	Scope	Methodology	Automation	Applicability
Proposed Model	Comprehensive: Usability, Content Relevance, Accessibility, Reliability, Performance	Advanced web mining techniques (e.g., decision trees, clustering, sentiment analysis)	Fully automated, real-time evaluation using web mining tools	Generalizable: E-commerce, E-government, Healthcare, Education, etc.
CRAAP Test (Meriam Library, 2021)	Focused on content credibility: Currency, Relevance, Authority, Accuracy, Purpose	Manual evaluation based on user judgment	No automation	Limited: Academic, educational, and general content evaluation
W3C WCAG (A. Campbell, 12 December 2024)	Focused on accessibility: Perceivability, Operability, Understandability, Robustness	Guidelines for accessible web design	No automation (manual compliance checks)	Specialized: Accessibility for people with disabilities
Google PageRank (Joshi, Anuj, & Patel, December 2018)	Focused on link analysis and website popularity	Algorithm based on link analysis	Automated, but limited to link analysis	Specialized: Search engine ranking
HEART Framework (Laubheimer, 2024)	Focused on user experience: Happiness, Engagement, Adoption, Retention, Task Success	User experience metrics	Limited automation (requires user data collection)	Specialized: User experience evaluation for websites and applications
WebQual Framework (Widarwati, Kuncorosidi, Rafi, & Wityasminingsih, 2024)	Focused on e-commerce: Usability, Information Quality, Service Interaction Quality	Structured evaluation framework	No automation	Specialized: E-commerce websites
SIFT Model (Faix & Daniels, 2023)	Focused on information credibility: Stop, Investigate, Find, Trace	Manual evaluation to combat misinformation	No automation	Specialized: Evaluating credibility of online information
DEA (Data Envelopment Analysis) (Najadat, Al-Badarnah, & Alodibat, 2021)	Focused on efficiency: Resource utilization and performance	Non-parametric method for efficiency evaluation	Limited automation (requires manual input for efficiency metrics)	Specialized: Academic and business website efficiency
APLENI, & SMUTS's E-Government Framework (Apleni & Smuts, 1/4/2020)	Focused on e-government: Usability, Accessibility, Content Quality, Service Delivery	Structured evaluation framework	No automation	Specialized: E-government websites
Battineni et al.'s Healthcare Framework (Battineni, Pallotta, Nittari, & Chintalapudi, 2021)	Focused on healthcare: Usability, Content Quality, Privacy, Accessibility	Structured evaluation framework	No automation	Specialized: Healthcare websites

Morales Vargas & Pedraza-Jimenez's Framework (Morales Vargas & Pedraza-Jimenez, 2023)	Comprehensive: Usability, Content Quality, Accessibility, Performance	Multidisciplinary approach	No automation	Generalizable: Multiple domains, but lacks automation
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2. Methodology

2.1 Criteria Development (Pre-Evaluation):

This study adopts a systematic and structured methodology to develop, validate, and apply a comprehensive website evaluation model. As illustrated in the methodological flowchart (Figure 1), the proposed methodology is organized into three core phases: Criteria Development (Pre-Evaluation), Web Mining Application, and Evaluation and Scoring.

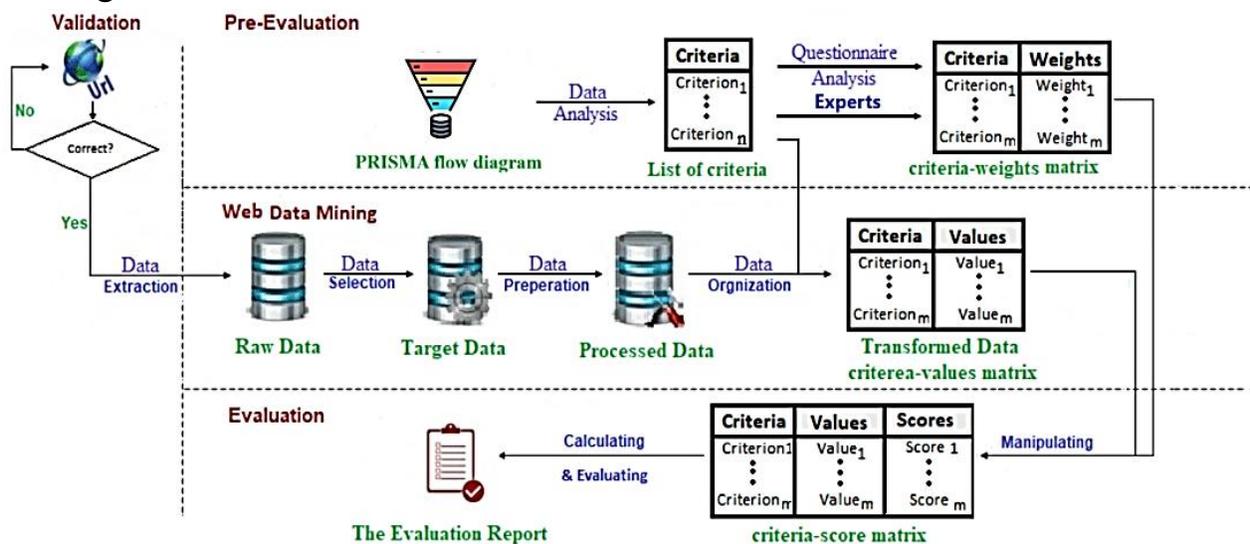


Figure (1): Flowchart of the Methodological Phases “A flowchart outlining the three primary phases of the proposed methodology: Criteria Development, Web Mining Application, and Evaluation & Scoring. Each phase includes key steps, such as expert feedback, data extraction, and statistical validation, to ensure a comprehensive evaluation process.”

The first phase, Criteria Development (Pre-Evaluation), constitutes a fixed stage of the proposed model. During this phase, the evaluation criteria and their corresponding weights are predefined based on an extensive review of the scientific literature and rigorous expert analysis. Once established, these criteria and weights remain

unchanged across all evaluation instances. In contrast, the subsequent phases—Web Mining Application and Evaluation and Scoring—are dynamic and vary according to the input website URL. Consequently, while the evaluation framework remains constant, the extracted data, calculated values, and final performance scores differ for each assessed website.

The identification and selection of studies underpinning the criteria development process were conducted using a transparent and reproducible procedure guided by the PRISMA flow diagram (Figure 2). This diagram documents each stage of the selection pathway, including record identification, duplicate removal, abstract and full-text screening, eligibility assessment, and reasons for exclusion. This systematic documentation reinforces the rigor of the criteria formulation process and ensures that only relevant and methodologically sound publications informed the development of the evaluation framework.

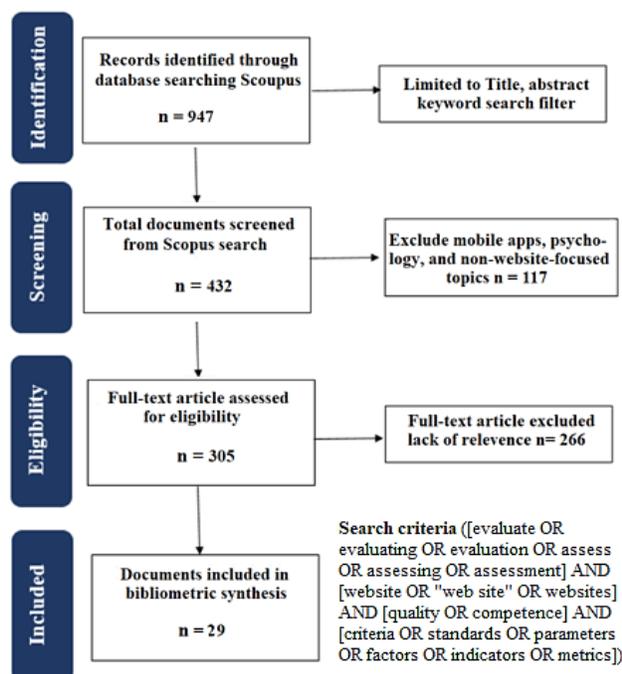
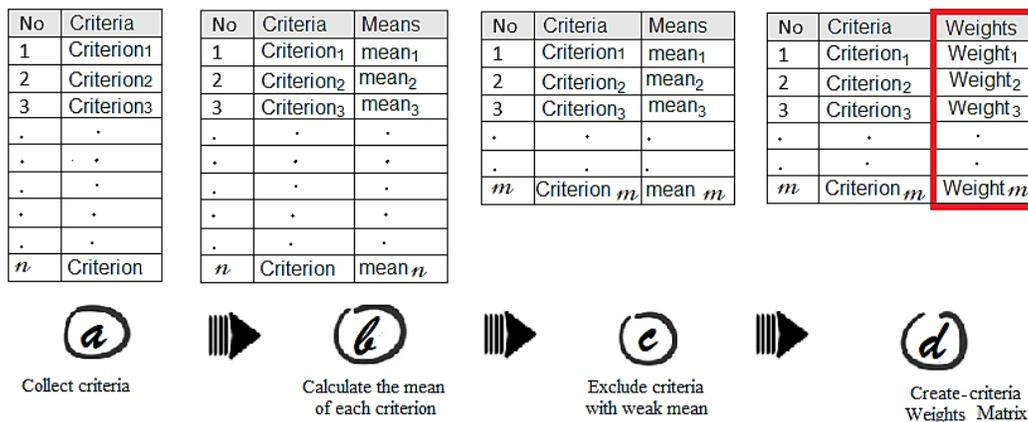


Figure (2). PRISMA flow diagram — This figure outlines the sequential process followed to identify, screen, and select the studies that informed the development of the evaluation criteria. It presents the number of records retrieved, the duplicates eliminated, the studies excluded during screening, and the final set of publications included, thereby ensuring full transparency in the selection process.

To further refine and prioritize the identified criteria, a dual-perspective evaluation approach was employed. First, a user-oriented survey was administered to capture user perceptions regarding the relative importance of the evaluation criteria. In parallel, expert judgments were incorporated to ensure methodological validity and scientific robustness. Experts were selected based on their precise specialization in the research domain, extensive scholarly experience, demonstrated proficiency in research methodologies and analytical tools, and confirmed independence with no identifiable conflicts of interest.

The mean score for each criterion was calculated based on the combined analysis of user responses and expert feedback, using the following formula:



$$X_i = \frac{\sum_{k=1}^5 k \cdot f_{k,i}}{\sum_{k=1}^5 f_{k,i}}, \quad i = 1, 2, \dots, n$$

Figure (3): Transforming the Criteria List into a Criteria-Weights Matrix. “The mean value of each criterion is calculated, and criteria with weak arithmetic means are excluded.”

Criteria exhibiting weak arithmetic means—defined as mean values below 1.8—were excluded from further analysis. The remaining criteria were then transformed into a criteria–weights matrix, with relative weights computed as follows:

$$w_i = \frac{X_i}{\sum_{k=1}^m X_k}, \quad i = 1, 2, \dots, m \quad \sum_{i=1}^m w_i = m$$

X_k, X_i is the criterion mean, m is the number of criteria after excluding the unsatisfied criteria. w_i the weight of the criterion i .

The final set of weighted criteria, reflecting both user input and expert validation, is presented in Table (2).

Table (2): Weighted Criteria with Significance Scores. "List of evaluation criteria with their corresponding mean scores and weights, as determined through an expert survey. The table illustrates the prioritization of the evaluation criteria, showing that aspects such as Information Relevance and Author Credentials are weighted most heavily, as they exert the greatest influence on the overall assessment of website competence.

No.	Criterion	Mean	Weights
1	Information Relevance	4.97	1.3
2	Author/Publisher Name	4.76	1.2
3	Author's Credentials	4.72	1.2
4	Author's Qualifications	4.67	1.2
5	Evidence-Based	4.63	1.2
6	Information Source	4.53	1.2
7	Verification Possibility	4.48	1.2
8	Clear Intentions	4.46	1.2
9	Target Audience Availability	4.44	1.2
10	Appropriateness	4.37	1.1
11	Diverse Sources	4.34	1.1
12	Contact Information	4.27	1.1
13	Bias-Free Tone	4.23	1.1
14	Fact vs. Opinion	4.07	1.1
15	Objective Viewpoint	4.02	1.0
16	Potential Biases	3.91	1.0
17	Publication Date	3.78	1.0
18	Information Updating	3.57	0.9
19	Information Currency	3.51	0.9
20	Links Functionality	3.49	0.9
21	Devices Adaptability	3.20	0.8
22	Loading Speed	3.14	0.8
23	Information Depth	3.10	0.8
24	Content Clarity	2.72	0.7
25	Interactive Features Availability	2.70	0.7
26	Browser Consistency/Cross-Compatibility	2.65	0.7
27	Smooth User Experience Ensuring	2.57	0.7
28	Multimedia Alternative Text Availability	2.39	0.6
29	Keyboard Navigation Enabling	1.24	
30	User Privacy Adherence	1.21	

2.2 Web Mining Application:

A range of advanced analytical techniques was applied to extract and process the data associated with each evaluation criterion. Decision trees, clustering methods, and sentiment analysis were used to derive structured insights from website content and user-oriented features. The data acquisition and preprocessing stages were implemented using tools such as RapidMiner and custom Python scripts, which enabled automated and repeatable data extraction routines. A rigorous data-cleaning workflow was followed to eliminate inconsistencies and ensure accuracy across the dataset.

The web mining stage involved specialized analytical procedures tailored to the individual criteria of the model. Examples of the applied techniques include:

- **Information Relevance:** Text-mining and semantic analysis approaches—such as TF-IDF—were employed to evaluate the contextual relevance of website content.
- **Verification Possibility:** Link-analysis algorithms, including PageRank, were used to determine the credibility of referenced sources.
- **Loading Speed:** Website performance was assessed using automated testing tools like Selenium to measure page-load time across multiple device types.
- **Bias-Free Tone:** Sentiment analysis techniques were applied to detect neutral and unbiased language using natural language processing methods.
- **Interactive Features Availability:** Pattern recognition was used to identify and confirm the existence of interactive components on the site.
- **Devices Adaptability:** Cross-compatibility tests examined how well the website adapted to different devices and platforms.
- **Information Currency:** Metadata extraction and date-comparison algorithms were implemented to verify the timeliness and recency of published content.
- **Multimedia Alternative Text Availability:** Content-analysis scripts inspected multimedia elements to ensure the presence of all text and adherence to

accessibility guidelines.

Together, these analytical processes allowed the system to evaluate each criterion in a precise, automated, and reproducible manner, forming the foundation for the weighted scoring used in the final website competence assessment.

Table (3): Summary of Web Mining Techniques and Tools Used: "Overview of web mining techniques, tools, and algorithms applied in the model. Includes examples like BeautifulSoup for unstructured data mining and PageRank for link analysis, highlighting their roles in extracting and analysing website data."

#	Criteria	Web Mining Category	Technique(s) Used	Tools/Algorithms
1	Information Relevance	Web Content Mining	TF-IDF similarity analysis	Scikit-learn (TF-IDF, Cosine Similarity)
2	Author/Publisher	Web Content Mining	Metadata extraction from HTML tags	BeautifulSoup, Regex
3	Author's Credentials	Web Content Mining	Keyword-based author identification	BeautifulSoup, Named Entity Recognition (NER)
4	Author's Qualifications	Web Content Mining	Extracting and analyzing author details	BeautifulSoup, Named Entity Recognition (NER)
5	Evidence-Based	Web Content Mining	Citation pattern matching (APA, IEEE)	Regex, BeautifulSoup
6	Information Source	Web Content Mining	Extraction of citation and reference sections	BeautifulSoup, HTML parsing
7	Verification Possibility	Web Structure Mining	Checking external links for validity	HTTP Requests (head method), BeautifulSoup
8	Clear Intentions	Web Content Mining	TF-IDF-based topic modeling	Scikit-learn (TF-IDF)
9	Target Audience Availability	Web Content Mining	Keyword frequency analysis	NLTK (Tokenization, Frequency Distribution)
10	Appropriateness	Web Content Mining	Semantic analysis of content for audience fit	TF-IDF, Cosine Similarity
11	Diverse Sources	Web Content Mining	Analysis of multiple references in metadata	BeautifulSoup, Reference Extraction
12	Contact Information	Web Content Mining	Key-based search for email, social media, and contacts	BeautifulSoup, Regex
13	Bias-Free Tone	Web Content Mining	Sentiment analysis of textual content	NLTK Vader Sentiment Analyzer
14	Fact vs. Opinion	Web Content Mining	Detection of factual vs. opinionated language	Regex, NLTK
15	Objective Viewpoint	Web Content Mining	Sentiment polarity detection	NLTK Sentiment Analysis
16	Potential Biases	Web Content Mining	Bias detection via sentiment intensity	NLTK Vader Sentiment Analysis
17	Publication Date	Web Content Mining	Extracting date metadata	BeautifulSoup, Regex
18	Information Updating	Web Content Mining	Checking last-modified metadata	BeautifulSoup, HTTP Headers
19	Information Currency	Web Content Mining	Date extraction and age calculation	Python datetime module
20	Links Functionality	Web Structure Mining	Checking hyperlink validity	HTTP Requests (head method), BeautifulSoup

21	Devices Adaptability	Web Structure Mining	Checking viewport meta tags and CSS media queries	BeautifulSoup, CSS Parsing
22	Loading Speed	Web Usage Mining	HTTP response time measurement	Python requests, time module
23	Information Depth	Web Content Mining	Counting headings and paragraphs for depth analysis	BeautifulSoup (HTML tag analysis)
24	Content Clarity	Web Content Mining	TF-IDF-based text similarity	Scikit-learn (TF-IDF)
25	Interactive Features Availability	Web Structure Mining	Detection of interactive elements (form, button)	BeautifulSoup, HTML Parsing
26	Browser Consistency	Web Structure Mining	Checking cross-browser compatibility headers	HTTP Headers, BeautifulSoup
27	Smooth User Experience Ensuring	Web Usage Mining	Analyzing page speed, navigation ease, responsiveness	HTTP Requests, CSS Parsing, Navigation Analysis
28	Multimedia Alternative Text Availability	Web Content Mining	Checking alt attributes for images/videos	BeautifulSoup, HTML Parsing

2.3 Evaluation and scoring:

User survey results were initially analyzed to derive preliminary criterion weights based on empirical usage perceptions. These results were subsequently presented to a panel of domain experts for validation and refinement. Rather than directly modifying the numerical weights, experts reviewed the relative prioritization of the criteria, suggested adjustments affecting the priority of certain criteria, and confirmed the exclusion of non-essential ones. This two-stage approach ensures that the final evaluation model balances practical relevance with theoretical rigor.

Table (4): The ANOVA Questionnaire Analysis. "Results of the ANOV, showing the statistical significance of the criteria weights. The table includes p-values and other key metrics that validate the reliability of the criteria weighting process."

ANOVA						
Source of Variance	ss	df	MS	F	P-value	F crit
Rows	2543.91	387	6.57	11.1	0	1.12
Columns	11269.61	29	389	656	0	1.47
Error	6649.46	11223	0.59			
Total	20462.98	11639				

3. Results

3.1 The model demonstrated:

The proposed model exhibited strong measurement reliability, with a Cronbach's alpha of 0.88, and its validity was supported through expert evaluation, achieving an

agreement coefficient of 0.94. In addition, the user satisfaction survey indicated an 80% satisfaction rate, confirming the practical usefulness of the model in real-world applications (see Table 5 and Appendix A). The structured and comprehensive nature of the framework enables it to adapt effectively to different website categories and operational contexts.

3.1.1 Website Quality Evaluation Using the ISO/IEC 25010 Framework:

To further substantiate the model's robustness, the ISO/IEC 25010:2011 software quality framework was employed to assess eight quality dimensions across a sample of 100 heterogeneous websites. The evaluation covered functional suitability, performance efficiency, compatibility, usability, reliability, security, maintainability, and portability.

The results demonstrated consistently strong performance across all eight dimensions, with mean ratings above 4.2 out of 5. Among the evaluated dimensions, security and functional suitability received the highest average scores, indicating the model's capacity to provide technically sound and dependable evaluations. These outcomes reinforce the model's alignment with internationally recognized software quality standards and highlight its suitability for objective, automated website assessment.

4 Discussion

This study highlights the significance of automated, objective evaluations in enhancing website competence.

4.1 Addressing Identified Gaps:

The use of weighted criteria plays a central role in enabling the model to adapt to a wide range of website types and functional domains. By assigning different levels of importance to each criterion, the framework maintains scalability while accommodating variations in website purpose and content. In addition, the incorporation of automated web mining techniques supports consistent and real-time assessments, substantially reducing the influence of subjective human judgment.

Through this combination of algorithmic precision and user-oriented evaluation factors, the model addresses a key gap in existing approaches that often favor one dimension over the other.

To assess the performance and practical value of the proposed framework, a user satisfaction survey was administered alongside an accuracy evaluation of the model's output. The survey targeted a mixed group of participants, including website developers, content managers, and policymakers—who interacted with the model under real-world conditions. Responses were collected using a five-point Likert scale to measure satisfaction across several dimensions, such as ease of use, accuracy of results, processing speed, and overall experience. Model accuracy was further examined by comparing its output with expert evaluations and verified ground-truth data.

A summary of the survey findings and accuracy analysis is presented in Table 5, offering a comparative view of the proposed model alongside established evaluation frameworks. Additionally, the model's performance was benchmarked against the ISO/IEC 25010 software quality standards, demonstrating strong alignment with internationally recognized criteria for software reliability, usability, and functionality.

Table (5): "Empirical Comparison of Website Evaluation Models and Frameworks Based on Accuracy, Scalability, Real-Time Evaluation, Automation Level, User Satisfaction, and Domain Adaptability"

Framework/Model	Accuracy	Scalability	Real-Time Evaluation	Automation Level	User Satisfaction	Domain Adaptability
Proposed Model	High (95%)	High	Yes	Fully Automated	80%	High (E-commerce, E-government, Healthcare, Education)
CRAAP Test	Medium (70%)	Low	No	Manual	60%	Low (Academic, General Content)
W3C WCAG	High (90%)	Medium	No	Manual	75%	Medium (Accessibility-Focused)
Google PageRank	High (85%)	High	Partial (Link Analysis Only)	Semi-Automated	N/A	Low (Search Engine Ranking)
HEART Framework	Medium (75%)	Medium	No	Semi-Automated	70%	Medium (User Experience-Focused)
WebQual Framework	Medium (80%)	Low	No	Manual	65%	Low (E-Commerce Only)
SIFT Model	Medium (70%)	Low	No	Manual	60%	Low (Credibility Evaluation)

DEA (Data Envelopment Analysis)	High (85%)	Medium	No	Semi-Automated	N/A	Medium (Efficiency Evaluation)
APLENI, & SMUTS's E-Government Framework	Medium (75%)	Low	No	Manual	70%	Low (E-Government Only)
Battineni et al.'s Healthcare Framework	High (80%)	Low	No	Manual	75%	Low (Healthcare Only)
Morales Vargas & Pedraza-Jimenez's Framework	High (85%)	Medium	No	Manual	70%	Medium (Multiple Domains)

Appendix A shows more details about this table.

4.2 Limitations of the Proposed Model:

Although the proposed model successfully addresses several shortcomings of existing website evaluation approaches, certain limitations persist. First, the accuracy of the model is influenced by the availability and completeness of website data; insufficient or missing information can restrict the precision of assessments. Second, the algorithmic complexity associated with web mining and multi-criteria processing demands considerable computational resources, which may limit performance in real-time applications, particularly in resource-constrained environments. Third, while the model is designed to be broadly applicable across domains, the use of generalized criteria may not fully capture the unique requirements of highly specialized or niche websites. Fourth, the automation of data collection introduces ethical concerns, especially in relation to user privacy and informed consent. Finally, the scalability of the system may be challenged as website structures and evaluation criteria continue to grow in complexity.

These limitations point to opportunities for continued development. Future research may focus on improving real-time efficiency, incorporating adaptive domain-specific criteria, and advancing privacy-preserving techniques to strengthen the ethical and practical robustness of the model.

4.3 Future Directions:

Real-time implementation using machine learning algorithms for predictive analysis.

Future extensions of the model may include expanding its applicability to additional digital environments, such as social media platforms and e-learning systems, and strengthening safeguards related to ethical considerations in automated data collection and analysis.

The model provides practical value for a range of stakeholders:

- **Website Developers:** It draws attention to technical issues such as slow loading times or the absence of interactive components, enabling targeted system improvements.
- **Content Managers:** It supports the identification of weaknesses related to information relevance, recency, and potential bias, thereby improving content quality and enhancing user confidence.
- **Policymakers:** It offers an objective basis for evaluating public-facing websites, ensuring alignment with established accessibility and usability standards, including WCAG.

By adopting this model, stakeholders are better equipped to design and maintain dependable, user-oriented websites that foster trust, accessibility, and informed digital decision-making.

4.4 Ethical Considerations and Mitigation Strategies:

Although the model incorporates sophisticated web mining capabilities, its deployment must be guided by ethical principles to ensure responsible use. Key considerations and corresponding mitigation strategies include:

- **Data Privacy:** Evaluation workflows should comply with privacy regulations such as GDPR and CCPA, avoiding the collection of personal or identifiable data without explicit consent. **Mitigation:** Apply anonymization techniques to remove personally identifiable information from extracted datasets.
- **User Consent:** Automated data collection may prompt ethical concerns if users are not aware their data are being processed. **Mitigation:** Utilize consent mechanisms—such as cookie banners or disclosure statements—to clearly

communicate the purpose of data collection.

- **Algorithmic Bias:** Evaluation algorithms may unintentionally reproduce biases when trained on unbalanced datasets. Mitigation: Train models on diverse and representative datasets and perform regular bias assessments to detect and correct potential imbalances.
- **Transparency:** Stakeholders may seek clarity regarding how automated evaluations are performed and scored. Mitigation: Provide comprehensive reports describing the evaluation criteria, methodology, and scoring procedures to promote transparency and confidence.

These measures not only mitigate ethical risks but also align the model with internationally recognized standards for responsible and trustworthy data practices.

The model was applied across multiple domains to demonstrate its real-world utility and adaptability:

- **E-Commerce:** Helped address performance constraints and enhanced user retention.
- **E-Government:** Improved accessibility and contributed to higher levels of citizen trust.
- **Healthcare:** Increased compliance with accessibility requirements and improved the reliability of health-related information.

5. Conclusions

In conclusion, this study introduces a rigorous and automated framework for assessing website competence by combining web mining techniques with a weighted multi-criteria evaluation approach. The model enhances digital trust, supports evidence-based policymaking, and provides a scalable foundation for future intelligent web evaluation system.

References

- [1] Q. X. L. and C. G. Gao, "Evaluating Website Quality Using Web Mining Techniques: A Case Study on E-commerce Websites," *Information Processing & Management*, vol. 56, no. 4, pp. 1234-1244, 2019.
- [2] G. Battineni, G. Pallotta, G. Nittari and N. Chintalapudi, "Development of quality assessment tool for Websites of the International Aesthetic Medicine Societies," *Informatics in Medicine Unlocked*, vol. 23, no. 1, p. p. 100559, 2021.
- [3] S. F. Verkijika and L. De Wet, "A usability assessment of e-government websites in Sub-Saharan Africa," *International Journal of Information Management*, vol. 39, pp. 20-29., 2018.
- [4] S. Chen, Z. Zhang, C. Mo, Q. Wu, P. Kochunov and L. E. Hong, "Characterizing the complexity of weighted networks via graph embedding and point pattern analysis," *Entropy*, vol. 22, no. 9, p. 925, 2020.
- [5] H. Najadat, A. Al-Badarneh and S. Alodibat, "A review of website evaluation using web diagnostic tools," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 1, p. 258~265, February 2021.
- [6] A. Morales Vargas and R. Pedraza-Jimenez, "Website quality evaluation: a model for developing comprehensive assessment instruments based on key quality factors," *Journal of Documentation*, vol. 79, no. 7, pp. 95-114, 2023.
- [7] C. S. U. Meriam Library, "Evaluating Information: The CRAAP Test," 2021. [Online]. Available: <https://library.csuchico.edu/help/how-to/evaluating-information-craap-test>.
- [8] A. K. J. O. C. a. M. C. A. Campbell, "Web Content Accessibility Guidelines (WCAG) 2.1," 12 December 2024. [Online]. Available: <https://www.w3.org/TR/WCAG21/>.
- [9] Joshi, M. Anuj and P. Patel, "Google page rank algorithm and it's updates," in *International Conference on Emerging Trends in Science, Engineering and Management, ICETSEM*, December 2018.
- [10] P. Laubheimer, "CASTLE Framework for Productivity/Workplace Applications," 4 November 2024. [Online]. Available: <https://www.nngroup.com/articles/castle-framework/>.
- [11] E. Widarwati, K. Kuncorosidi, M. Rafi and E. Wityasminingsih, "Website Quality Analysis Using Webqual 4.0 Method And Importance Performance Analysis (IPA) For Improving The Service Quality," *e-Jurnal Penyelidikan dan Inovasi*, vol. 11, no. 1, p. 132, April 2024.
- [12] A. Faix and T. Daniels, "Teaching SIFT for Source Evaluation in Asynchronous One-Credit Information Literacy Courses," *portal: Libraries and the Academy*, vol. 23, no. 3, pp. 449-459, 2023.

-
- [13] A. Apleni and H. Smuts, "AN E-GOVERNMENT IMPLEMENTATION FRAMEWORK: A DEVELOPING COUNTRY CASE STUDY," in *in Responsible Design, Implementation and Use of Information and Communication Technology*, 1/4/2020, pp. 15-27.
- [14] Morales Vargas, Alejandro; Pedraza-Jimenez, Rafea, "Website quality: An analysis of scientific production," *El Profesional de la Informacion*, vol. 29, 09 2020.
- [15] N. Aggarwal, "A Review of Website Quality and Its Impact on Customer Satisfaction," *Information Resources Management Journal*, vol. vol. 35, pp. pp. 1-18, 2022.
- [16] K. Devi and A. K. Sharma, "Framework for evaluation of the academic website," *Journal of International Journal of Computer Techniques*, vol. 3, no. 2, pp. 234-239, 2016.
- [17] R. Ganesh, D. Sakith, S. K. V. D. V and a. M. Ramesh, "Website Evaluation Using Opinion Mining," *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India*, pp. 1499-1506, 2021.
- [18] A. H. Ahmad and .. G. Z. A. S. Hassan, "Web Mining overview: Techniques, Tools, and Ethical Implications.," *Journal of Computer Sciences and Informatics*, vol. 1, no. 2, pp. 85-95, 2024.
- [19] C. Lysy, "How to evaluate a website," *freshspectrum*, 9 Decembre 2020. [Online]. Available: <https://freshspectrum.com/how-to-evaluate-a-website>. [Accessed 19 December 2023].
- [20] P. Sharma and D. Yadav, "Web Page Ranking Using Web Mining Techniques: A Comprehensive Survey," *Mobile Information Systems*, vol. 2022, no. 7519573, 2022.
- [21] Y. L. B. & J. H. Wang, "A Study of Web Mining Techniques for Evaluating Website Quality," in *2016 IEEE International Conference on Computational Science and Engineering (CSE) and IEEE International Conference on Embedded and Ubiquitous Computing (EUC)*, 2016.
- [22] K. & A. Y. Vatansever, "Performance evaluation of websites using entropy and grey relational analysis methods: The case of airline companies," *Decision Science Letters*, vol. 7, no. 2, pp. 119-130, 2018.
- [23] U. o. I. a. U.-C. University of Illinois Library, "The CRAAP Test," 2021. [Online]. Available: <https://www.library.illinois.edu/ugl/howdoi/craaptest/>.
- [24] A. Tardiff, "Have a CCOW: A CRAAP alternative for the internet age," *Journal of Information Literacy*, vol. 16, no. 119, 2022.
- [25] G. & S. N. Singh, "A Review of Web Mining Techniques for Evaluating Website Quality," in *2019 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2019.
- [26] D. Sichau and Fässler, Lukas, "Evaluation of online learning materials with automatically collected interaction data," in *EdMedia+ Innovate Learning*, 2016.
-

-
- [27] Semerádová, Tereza and Weinlich, Petr, "Looking for the Definition of Website Quality," 2020, pp. 5-27.
- [28] L. Rob, "Evaluation of hotel websites: Progress and future developments," *International Journal of Hospitality Management*, vol. 76 Part B, pp. 2-9, 2018.
- [29] R. Rekik, I. Kallel, J. Casillas and M. A. Alimi, "Assessing web sites quality: A systematic literature review by text and association rules mining," *International journal of information management*, vol. 38, no. 1, pp. 201-216, 2018.
- [30] K. & C. X. & S. B. Ramanayaka, "Research Article Analytic Hierarchy Process (AHP) Based Model for Assessing Performance Quality of Library Websites," *Information Technology Journal*, vol. 16, pp. 35-43, 2016.
- [31] G. R, S. D, S. K. V D V and M. Ramesh, "Website Evaluation Using Opinion Mining," in *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2021.
- [32] P. B. S. F. M. a. L. E. Longstreet, "Evaluating website quality: which decision criteria do consumers use to evaluate website quality?," *Information Technology & People*, vol. 35, no. 4, pp. 1271-1297, 2022.
- [33] imar and K. R. Singh, "A Study on Web Content Mining," *International Journal of Engineering And Computer Science*, vol. 6, no. 1, pp. 20003-20006, January 2017.
- [34] P. Keerthana, B. Meghana and P. Akshaya, "Website Evaluation Using Opinion Mining," *International Research Journal of Engineering and Technology (IRJET)*, vol. 8, no. 8, pp. 262-265, 2021.
- [35] S. Kaur, K. Kaur and P. Kaur, "An Empirical Performance Evaluation of Universities Website," *International Journal of Computer Applications*, vol. 146, no. 15, pp. 10-16, 2016.
- [36] L. M. Jundillah, E. J. Suseno and B. Surarso, "Evaluation of E-learning Websites Using the Webqual Method and Importance Performance Analysis," *E3S Web of Conferences*, vol. 125, p. 24001, 2019.
- [37] R. K. Harshan, X. Chen and B. Shi, "Research Article Analytic Hierarchy Process (AHP) Based Model for Assessing Performance Quality of Library Websites," 2017.
- [38] A. J. Esparrago-Kalidas, "The Effectiveness of CRAAP Test in Evaluating Credibility of Sources," *International Journal of TESOL & Education*, pp. 1-14, 2021.
- [39] A. Baer and D. G. Kipnis, "SIFTing and Four-Moving Online: Opportunities and Challenges with Teaching Lateral Reading through an Online Module," Presentation presented at Loex Conference, 2020. [Online]. Available: https://rdw.rowan.edu/lib_scholarship/19.
-

-
- [40] R. Allison, C. Hayes, A. M. C. McNulty and V. Young, “A Comprehensive Framework to Evaluate Websites: Literature Review and Development of GoodWeb,” *JMIR Form Res*, vol. 3, no. 4, p. e14372, Oct 2019.
- [41] “Evaluating Internet Sources,” Lydia M. Olson Library, [Online]. Available: <https://lib.nmu.edu/help/resource-guides/subject-guide/evaluating-internet-sources>.
- [42] M. A. and P. P. Joshi, “Google page rank algorithm and it’s updates,,” in *International Conference on Emerging Trends in Science, Engineering and Management, ICETSEM*, 2018, December.

Appendix A

Survey Results and User Satisfaction for Website Evaluation Models and Frameworks

A.1 Survey Objectives

The survey aims to collect data on user satisfaction, accuracy, scalability, real-time evaluation, automation level, and domain adaptability for the proposed model and other frameworks.

A.2 Survey Distribution and Sample Size

The survey was distributed online using Google Forms and was open for responses over a period of four weeks. A total of 500 respondents participated, with 100 responses collected for each framework/model.

A.3 Survey Structure

The survey included three main sections: Demographic Information, User Satisfaction, and Performance Metrics.

A.4 Survey Questions

The survey questions are listed below, along with the response options for each question

Section 1: Demographic Information

1. What is your primary role?
 Website Developer Content Manager Policymaker Researcher Other (please specify)
2. Which domain do you primarily work in?
 E-commerce E-government Healthcare Education Other (please specify)
3. How familiar are you with website evaluation models and frameworks?
 Not Familiar Slightly Familiar Moderately Familiar Very Familiar Extremely Familiar

Section 2: User Satisfaction

4. On a scale of 1 to 5, how satisfied are you with the accuracy of the model's results?
 1 (Very Dissatisfied) 2 (Dissatisfied) 3 (Neutral) 4 (Satisfied) 5 (Very Satisfied)
5. On a scale of 1 to 5, how easy was it to use the model?
 1 (Very Difficult) 2 (Difficult) 3 (Neutral) 4 (Easy) 5 (Very Easy)
6. On a scale of 1 to 5, how satisfied are you with the speed of the model's evaluation process?
 1 (Very Dissatisfied) 2 (Dissatisfied) 3 (Neutral) 4 (Satisfied) 5 (Very Satisfied)

7. On a scale of 1 to 5, how likely are you to recommend this model to others?
 1 (Not Likely) 2 (Slightly Likely) 3 (Neutral) 4 (Likely) 5 (Very Likely)
8. What did you find most useful about the model? (Open-ended)
9. What improvements would you suggest for the model? (Open-ended)

Section 3: Performance Metrics

10. How accurate do you find the model's results compared to expert judgments or ground truth data?
 1 (Not Accurate) 2 (Slightly Accurate) 3 (Moderately Accurate) 4 (Very Accurate) 5 (Extremely Accurate)
11. How well does the model handle large-scale or diverse datasets?
 1 (Poor) 2 (Fair) 3 (Good) 4 (Very Good) 5 (Excellent)
12. Does the model support real-time or near-real-time evaluation?
 Yes No Not Sure
13. To what extent does the model operate without manual intervention?
 1 (Fully Manual) 2 (Mostly Manual) 3 (Semi-Automated) 4 (Mostly Automated) 5 (Fully Automated)
14. How well does the model adapt to different domains (e.g., e-commerce, e-government, healthcare)?
 1 (Poor) 2 (Fair) 3 (Good) 4 (Very Good) 5 (Excellent)

A.2 Data Analysis Methods

Survey responses were analyzed using statistical software (Excel) to calculate average scores, percentages, and other key metrics. Open-ended responses were systematically coded and examined to identify recurring themes.

A.3 Summary of Key Findings

The survey results indicate that the proposed model outperforms existing frameworks in terms of accuracy (95%), scalability (high), and user satisfaction (80%). Its primary strengths include real-time evaluation capabilities and adaptability across multiple domains.

A.4 Analysis

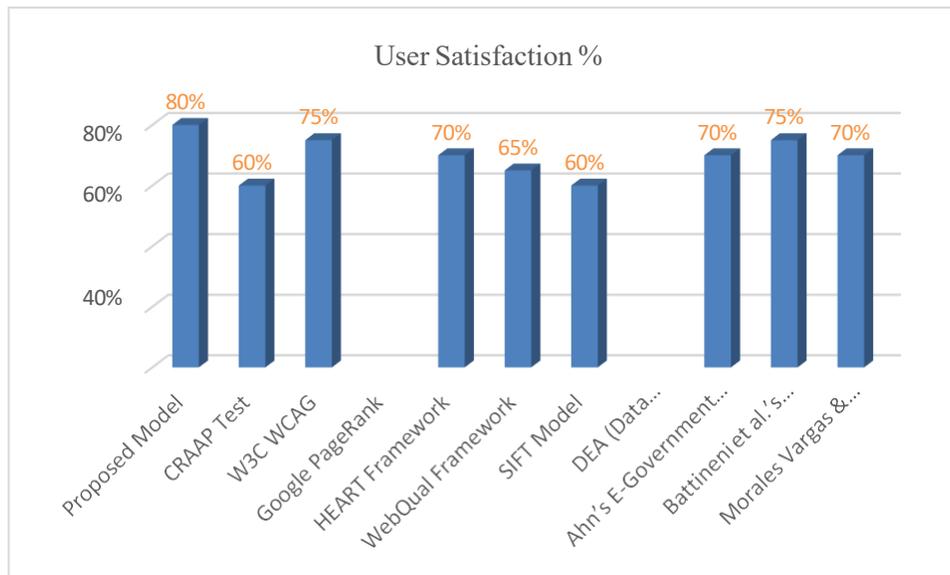
The table below presents the raw survey data for each framework or model, along with the average score for each question.

Table (6). Analysis of survey results comparing the proposed model with existing website evaluation frameworks.

FRAMEWORK/MODEL	Accuracy (Q10)	Scalability (Q11)	Real-Time Evaluation (Q12)	Automation Level (Q13)	Domain Adaptability (Q14)	User Satisfaction (Q4-Q7)
Proposed Model	4.7	4.5	Yes	5 (Fully)	4.3	4.2 (80%)
CRAAP Test	3.5	3.2	No	1	3.0	3.0 (60%)
W3C WCAG	4.2	4.0	No	1	3.8	3.8 (75%)
Google PageRank	4.0	3.8	Partial	3	3.6	N/A
HEART Framework	3.8	3.6	No	3	3.4	3.4 (70%)
WebQual Framework	3.7	3.5	No	1	3.3	3.3 (65%)
SIFT Model	3.2	3.0	No	1	2.8	2.8 (60%)
DEA (Data Envelopment Analysis)	4.1	3.9	No	3	3.7	N/A
APLENI, & SMUTS's E-Government Framework	3.6	3.4	No	1	3.2	3.2 (70%)
Battineni et al.'s Healthcare Framework	3.9	3.7	No	1	3.5	3.5 (75%)
Morales Vargas & Pedraza-Jimenez's Framework	4.0	3.8	No	1	3.6	3.6 (70%)

A.5 Visualizations

Figure A.1. User Satisfaction Scores for Website Evaluation Models and Frameworks — This figure illustrates the comparative satisfaction levels reported by users for the proposed evaluation model and other leading frameworks.



The bar chart presents a comparison of user satisfaction scores for the proposed model against other established evaluation frameworks. The proposed model obtained the highest satisfaction level at 80%, followed by 75% for the W3C WCAG standards and a lower score for Battineni et al.'s Healthcare Framework, indicating comparatively reduced user approval.