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AI-DRIVEN LIBRARY SERVICES: ASSESSING USER ENGAGEMENT, SATISFACTION, AND ACCESSIBILITY IMPACTS

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ABSTRACT
Artificial Intelligence (AI) is revolutionizing the way users interact with digital libraries by enabling personalized recommendations, intelligent search, and conversational virtual assistance. This study aims to assess the impact of AI-driven library services on user engagement, satisfaction, and information-seeking behavior, with a particular emphasis on improving accessibility for differently-abled users. A mixed-method approach involving user analytics, surveys, and accessibility testing was employed in an academic digital library environment. Results demonstrate a significant increase in engagement metrics (37%), higher satisfaction scores (4.6/5), and improved accessibility experiences for visually and hearing-impaired users. The findings suggest that AI-driven libraries enhance inclusivity and foster more active and personalized user participation in the information ecosystem.

Keywords: Artificial Intelligence, Library Services, User Engagement, Accessibility, Differently-Abled Users, Information Behavior.

I. INTRODUCTION

The rapid adoption of artificial intelligence (AI) in digital information environments is reshaping how libraries deliver services and support user information needs. Modern library systems increasingly incorporate AI modules — including personalized recommendation engines, semantic search, and conversational virtual assistants — to improve discovery, reduce search effort, and tailor content to individual preferences [1], [2]. These innovations promise to transform libraries from passive repositories into proactive, user-centered knowledge platforms that adapt to evolving user behavior and expectations [3].

While numerous technical studies describe algorithms and architectures for AI-enabled library functionalities, there is comparatively less empirical evidence on how these systems affect actual user behavior, engagement, and satisfaction in operational settings [4], [5]. Understanding user outcomes is particularly important because improvements in backend accuracy do not always translate to better user experiences; usability, trust, and perceived usefulness mediate the impact of AI features on continued adoption and engagement [6]. Furthermore, digital libraries serve diverse populations; evaluating how AI affects differently-abled users (e.g., visually impaired, hearing impaired, or users with motor limitations) is critical to ensuring equitable access and meeting accessibility mandates [7], [8].

Accessibility-oriented AI features — such as voice interfaces, text-to-speech, adaptive presentation, and multimodal assistants — show strong potential to reduce barriers for differently-abled patrons, increasing task success rates and independence in information seeking [9], [10]. At the same time, concerns about privacy, algorithmic bias, and explainability persist and can influence user trust and satisfaction, especially among vulnerable groups [11], [12]. Therefore, a holistic evaluation must combine objective engagement metrics (e.g., session duration, click-through, task completion) with subjective measures (e.g., satisfaction surveys, perceived ease-of-use) and targeted accessibility tests.

This study aims to assess the impact of AI-driven library services on user engagement, satisfaction, and information-seeking behavior, with a particular emphasis on accessibility gains for differently-abled users. We adopt a mixed-methods approach combining usage analytics, controlled usability tasks, and user surveys to (1) quantify changes in engagement and satisfaction after AI feature deployment, (2) evaluate accessibility outcomes for diverse user groups, and (3) surface qualitative insights about user perceptions, trust, and the practical trade-offs of AI adoption in libraries. By grounding technical advances in user-centered evaluation, the research seeks to inform principled deployment of AI in library ecosystems that is both effective and inclusive [13]–[15].

II. LITERATURE REVIEW

The increasing use of artificial intelligence (AI) in library systems has led to a paradigm shift in how users interact with digital knowledge environments. Early applications primarily focused on automation of cataloging, metadata generation, and indexing. However, recent studies emphasize the growing importance of AI-driven personalization, user engagement measurement, and accessibility-oriented design [16]. The literature reviewed here is organized into four themes: (1) AI integration in libraries, (2) personalization and user engagement, (3) AI for accessibility, and (4) ethical and behavioral implications.

Tan and Gupta (2024) [17] identified AI as a key enabler for modernizing digital library systems, highlighting its role in automating metadata tagging, enhancing retrieval accuracy, and improving decision support. Similarly, Ahmed and Nair (2023) [18] developed an AI-enabled management framework that employs natural language processing (NLP) to improve catalog consistency and metadata interoperability across digital repositories.

Wu, Liu, and Song (2024) [19] proposed a scalable neural classification model to automate subject indexing and topic identification, improving the speed and reliability of catalog management. Chowdhury and Leung (2024) [20] extended this idea through predictive analytics, showing that AI-based models could forecast circulation trends and optimize collection development in smart libraries. Collectively, these studies underscore the operational efficiency gains of AI, but few assess its behavioral impact on users — a gap this research aims to address.

Personalized recommendations and adaptive interfaces are central to enhancing library user engagement. Rahman et al. (2024) [21] demonstrated that hybrid recommendation engines combining collaborative and content-based filtering increased user satisfaction by 32% in an academic library setting. Furtado and Esmin (2023) [22] developed a dynamic recommendation model based on user tags and behavioral feedback, significantly improving information discovery rates.

Recent advances in deep learning and graph neural networks (GNNs) have further refined personalization. Yadav and Kumar (2025) [23] introduced a GNN-based system for smart libraries capable of modeling complex relationships between users and content, yielding higher engagement durations and relevance scores. Kaur, Verma, and Anand (2024) [24] applied user behavior analytics to predict reading patterns and recommend personalized study materials, leading to improved learning outcomes.

However, Zhang et al. (2023) [25] emphasized that while personalization increases engagement, it can also reinforce content bias and filter bubbles. Therefore, the balance between automation and diversity of exposure remains an open research area.

The integration of AI into accessibility technologies has become essential for equitable digital participation. O'Reilly and Klein (2024) [26] demonstrated that conversational agents using NLP significantly improved the experience of visually impaired library users by simplifying resource navigation. Similarly, Choudhury and Lee (2025) [27] proposed a multimodal AI assistant supporting both speech and tactile feedback, resulting in a 42% improvement in accessibility task success rates.

Patel and Kumar (2024) [28] explored NLP-driven virtual assistants in public libraries, noting that conversational AI reduced dependence on staff and enhanced self-efficacy among differently-abled patrons. Salameh (2024) [29] investigated how AI tools align with the Web Content Accessibility Guidelines (WCAG 2.1), revealing that voice recognition and text-to-speech features improved accessibility perception scores by 38%.

Despite these improvements, Liu et al. (2025) [30] cautioned that adaptive AI systems must ensure inclusivity in dataset design to avoid overlooking minority accessibility needs such as sign-language recognition or cognitive impairments. Therefore, ongoing research should focus on universal design principles, where AI systems accommodate all users by default rather than retrofitting accessibility features post-deployment.

B.V. Srinivasulu's recent contributions collectively emphasize intelligent diagnostic modeling and efficient health-record organization as dual pillars of modern healthcare analytics. In "Fuzzy Logic-Driven Machine Learning Algorithms for Improved Early Disease Diagnosis," the author integrates fuzzy rule-based inference with machine-learning classifiers to handle ambiguity and imprecise symptom patterns, demonstrating improved sensitivity in early-stage detection where clinical data are often noisy or incomplete [31]. Complementing this diagnostic focus, his work "Enhancing Healthcare Records Management With Efficient Graph Database Systems" proposes a graph-based architecture for electronic health records, showing that node–edge representations significantly enhance relationship querying, interoperability, and care-pathway analysis compared to traditional relational systems, thereby enabling faster and more context-aware retrieval of patient information [32]. Together, these studies highlight how uncertainty-tolerant diagnostic models and graph-centric data infrastructures can jointly strengthen accuracy, accessibility, and continuity of patient care. [31][32].

The two IEEE ICSSAS 2025 conference contributions collectively underscore the expanding role of machine learning and deep learning in strengthening cybersecurity and enhancing visual data interpretation. The work on "Adaptive Forged Phishing URL by Using Machine Learning" highlights how intelligent feature extraction, lexical–behavioral analysis, and adaptive classification models can identify evolving phishing URLs with greater precision, addressing the increasingly dynamic nature of online threats and improving real-time web security systems [33]. In parallel, the study on "Image Labeling Using CNN With Web Application" demonstrates the effectiveness of convolutional neural networks in automating image annotation and integrates these models

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into a web-based interface, enabling accessible and scalable visual-content management for end users [34]. Together, these conference studies show how AI-driven adaptive security mechanisms and deep-learning-based image understanding can significantly enhance digital safety and user interaction across modern web environments. [33][34].

III. RESEARCH METHODOLOGY

3.1 Research Design

This study adopts a mixed-method approach combining quantitative analytics and qualitative insights to comprehensively evaluate the impact of AI-driven library services. The objective was to measure changes in user engagement, satisfaction, and accessibility after implementing AI features such as personalized recommendations, semantic search, and interactive virtual assistance. The study was conducted over a four-week period in a university's digital library environment, with both pre-implementation and post-implementation comparisons.

The research design included three stages:

1. **Pre-assessment phase** – Baseline data collection on user engagement and satisfaction using traditional digital library systems.
2. **AI integration phase** – Deployment of AI-driven modules for personalization, semantic search, and virtual assistance.
3. **Post-assessment phase** – Measurement of behavioral changes, accessibility improvements, and user feedback after AI adoption.

3.2 Participants

A total of 150 participants were selected through purposive sampling to ensure representation from diverse user groups:

- **100 general users** (students, faculty, researchers)
- **50 differently-abled users**, including:
  - 25 visually impaired
  - 15 hearing impaired
  - 10 with motor or cognitive challenges

All participants had prior experience using digital library platforms. Informed consent was obtained, and accessibility accommodations (screen readers, speech-to-text tools, voice navigation) were provided during the study.

3.3 System Implementation

The AI-driven library system comprised three integrated components:

1. **Personalized Recommendation Engine** – Suggested books, journals, and media content based on user history, preferences, and reading patterns.
2. **AI-Driven Semantic Search** – Used natural language processing (NLP) and contextual embeddings to interpret user intent and return relevant results.
3. **Interactive Virtual Assistant** – Provided conversational support through both text and voice, enabling resource queries, navigation guidance, and accessibility assistance.

The backend was developed using Python, TensorFlow, and Hugging Face Transformers. The system's database stored metadata, user logs, and feedback, ensuring modular integration with the existing library management platform.

3.4 Data Collection

Data were collected using three primary methods:

1. **System Analytics** – Automatically captured quantitative data on user activity, including:
   - Session duration (average time spent per visit)
   - Click-through rate (CTR)
   - Search response time
   - Frequency of system use
   - Resource discovery success rate
2. **User Satisfaction Surveys** – A structured Likert-scale questionnaire (1–5 scale) was administered post-interaction to measure:
   - Ease of use

- Perceived usefulness
- Trust and satisfaction with AI features
- Accessibility experience for differently-abled users

3. **Interviews and Observations** – Semi-structured interviews were conducted to gain qualitative insights into user perceptions, challenges, and suggestions. Observational notes were taken during accessibility testing to record user interaction behaviors.

3.5 Evaluation Metrics

To evaluate system performance and impact, the following metrics were used:

A. User Engagement Metrics

- **Average Session Duration (ASD):** Measures how long users actively engage with the system per session.
- **Click-Through Rate (CTR):** Percentage of recommended or search results users clicked on.
- **Frequency of Visits (FV):** Tracks recurring user activity across sessions.

B. User Satisfaction Metrics

- **Satisfaction Index (SI):** Average user rating of system experience (1–5).
- **Perceived Usefulness (PU):** Self-reported assessment of system value in improving efficiency.
- **Ease of Interaction (EI):** Reflects interface intuitiveness and response speed.

C. Accessibility Metrics

- **Task Completion Rate (TCR):** Percentage of users (especially differently-abled) completing information-seeking tasks independently.
- **Accessibility Score (AS):** Evaluated on compliance with WCAG 2.1 standards (contrast, navigation, voice response).
- **Assistive Accuracy (AA):** Correctness of responses or actions performed by the virtual assistant for accessibility-related commands.

3.6 Data Analysis

- **Quantitative Analysis:**Data from analytics and surveys were analyzed using descriptive statistics and comparative analysis between pre- and post-AI results. Metrics such as mean, percentage improvement, and paired t-tests were used to identify statistically significant differences.
- **Qualitative Analysis:**Thematic coding was applied to interview transcripts to identify recurring patterns related to usability, accessibility, and trust in AI features. Themes were mapped to engagement metrics for interpretive correlation.
- **Accessibility Analysis:**Performance of assistive features (text-to-speech, voice recognition) was evaluated against benchmark accessibility guidelines to determine compliance and practical usability.

3.7 Ethical Considerations

All procedures adhered to institutional ethical standards. Participant data were anonymized, and consent was obtained prior to participation. Accessibility support was ensured for all differently-abled users. No personally identifiable information (PII) was collected, and the AI models did not store individual user conversations to maintain privacy and data protection compliance.

IV. RESULTS AND DISCUSSION

4.1 Overview

The deployment of AI-driven library services led to substantial improvements in user engagement, satisfaction, and accessibility outcomes. Quantitative system analytics were compared across pre-AI and post-AI implementation phases, while qualitative feedback provided deeper insights into behavioral changes and perceived usability.

Results show that the integration of **personalized recommendation**, **semantic search**, and **virtual assistance** significantly enhanced users' overall interaction experience.

4.2 Quantitative Results

4.2.1 User Engagement Metrics

Metric	Before AI Integration	After AI Integration	% Improvement
Average Session Duration (minutes)	7.3	10.2	+39.7%
Click-Through Rate (CTR)	42%	58%	+38.0%
Frequency of Visits per Week	2.4	3.8	+58.3%
Resource Discovery Success Rate	69%	90%	+30.4%

Interpretation:

Post-AI results demonstrate clear behavioral enhancement. Users spent longer per session, interacted more with recommendations, and visited the library more frequently. The AI recommendation engine improved discoverability by accurately matching user preferences and reading history. The semantic search further reduced irrelevant results, contributing to higher engagement and retrieval success.

4.2.2 User Satisfaction Metrics

Satisfaction Indicator	Before AI	After AI	Change (%)
Ease of Use	3.7 / 5	4.5 / 5	+21.6%
Perceived Usefulness	3.8 / 5	4.6 / 5	+21.1%
Interface Experience	3.9 / 5	4.7 / 5	+20.5%
Overall Satisfaction Index	**3.8 / 5**	**4.6 / 5**	**+21.0%**

Interpretation:

User feedback highlighted improved navigation, faster retrieval, and higher confidence in search results. The AI virtual assistant reduced user frustration during complex searches by providing contextual help and natural language guidance. Participants noted that the system felt "intuitive," "responsive," and "personalized," aligning with contemporary expectations of digital interaction.

4.2.3 Accessibility Performance Metrics

Accessibility Measure	Before AI System	After AI System	Improvement (%)
Task Completion Rate (Differently-Abled Users)	62%	88%	+41.9%
Accessibility Score (WCAG 2.1 Compliance)	71%	93%	+30.9%
Assistive Response Accuracy	74%	92%	+24.3%
User Independence Rating (Self-Reliance)	3.4 / 5	4.7 / 5	+38.2%

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Interpretation:

The accessibility results confirm that AI integration drastically improved inclusivity. Voice-enabled commands, adaptive interfaces, and text-to-speech features allowed visually impaired users to perform tasks independently. The multimodal assistant enhanced user autonomy and reduced dependence on library staff. Feedback from differently-abled users described the system as “empowering” and “life-changing,” as it enabled self-service and easy navigation through digital catalogs.

4.3 Qualitative Analysis

Interviews and open-ended survey responses provided valuable insights into user perceptions. The thematic analysis revealed three dominant themes:

1. **Enhanced User Engagement:**Users appreciated AI recommendations that aligned with their interests. Many noted that “relevant suggestions encouraged longer browsing sessions” and helped them discover new topics organically.
2. **Improved Accessibility and Inclusion:**Differently-abled participants emphasized how voice and speech-based features enhanced their independence. A visually impaired participant stated:

   > “Before, I relied on assistance to locate journals. Now, I can search, read summaries, and reserve items using voice commands alone.”
3. **Trust and Transparency:**While most users expressed high satisfaction, a small subset mentioned concerns about how their data was being used for recommendations. This highlights the importance of integrating explainable AI to increase transparency and trust in library contexts.

4.4 Comparative Behavioral Insights

Post-AI analytics indicated not just quantitative improvement but also qualitative shifts in user behavior:

- **Proactive engagement:** Users transitioned from passive searchers to active explorers.
- **Task autonomy:** Differently-abled users completed complex retrieval tasks without human help.
- **Information satisfaction:** Fewer users abandoned sessions mid-search, reflecting improved confidence in AI results.
- **Emotional connection:** Conversational agents created a sense of “interaction” rather than mere “transaction,” increasing retention.

4.5 Statistical Summary

Statistical analysis using paired t-tests confirmed that improvements in engagement ($p < 0.01$), satisfaction ($p<0.05$), and accessibility ($p<0.01$) were statistically significant.

This suggests that observed behavioral changes are not random but directly associated with the AI service integration.

The correlation coefficient between user satisfaction and average session duration was $r = 0.81$, indicating a strong positive relationship — users who found the system easier and more useful tended to spend more time engaging with resources.

4.6 Discussion

The findings support the hypothesis that AI-driven library services positively impact user engagement, satisfaction, and accessibility.

Compared to traditional systems, the AI-integrated model provides:

- Personalized experiences through adaptive recommendations.
- Intelligent discovery via semantic search mechanisms.
- Inclusive access through multimodal interaction support.

The research confirms that AI enhances both cognitive and emotional dimensions of library use — users feel understood, supported, and empowered. For differently-abled users, the inclusion of speech, audio, and adaptive UI features represents a major leap toward digital equity.

However, the study also emphasizes the need for continuous ethical governance — ensuring that personalization algorithms remain transparent, unbiased, and privacy-compliant.

V. CONCLUSION AND FUTURE WORK

CONCLUSION

This study assessed the impact of AI-driven library services on user engagement, satisfaction, and accessibility, particularly for differently-abled users. The integration of personalized recommendation engines, AI-driven semantic search, and virtual assistants led to measurable improvements in user interaction metrics. Results indicated a 39% increase in engagement, a 21% rise in satisfaction scores, and a 42% improvement in accessibility task success rates. Users reported that the AI system was more intuitive, adaptive, and inclusive, demonstrating how intelligent automation can transform digital libraries into proactive and equitable learning environments.

The findings confirm that AI enhances not only technical efficiency but also user confidence and independence, especially among visually and hearing-impaired users. The implementation of voice-enabled interaction, adaptive interfaces, and real-time conversational support significantly reduced accessibility barriers and improved information-seeking behavior. However, the study also highlights the importance of maintaining ethical AI governance, ensuring transparency, user privacy, and fairness in personalized recommendations.

FUTURE SCOPE

Future research should focus on real-world deployment across diverse library networks, including national and public libraries, to validate scalability and sustainability. Incorporating multilingual and multimodal AI systems, federated learning for privacy-preserving personalization, and generative AI models for automated content summarization could further enhance accessibility and engagement. Ultimately, AI-driven libraries hold the potential to create inclusive, intelligent, and user-centered ecosystems that democratize knowledge access for all members of society.

REFERENCES

[1] L. Tan and A. Gupta, “Artificial Intelligence Applications in Digital Library Systems: A Comprehensive Survey,” IEEE Access, vol. 12, pp. 20231–20248, 2024.

[2] R. Ahmed and P. S. Nair, “AI-Enabled Library Management Systems for Metadata Automation,” J. Inf. Technol. Serv., vol. 19, no. 1, pp. 66–79, 2023.

[3] C. Lee and S. Wu, “Digital Transformation in Academic Libraries: Challenges and Opportunities,” J. Libr. Inf. Sci., vol. 56, no. 2, pp. 145–160, 2023.

[4] T. B. Furtado and A. Esmin, “Hybrid Content Dynamic Recommendation System Based in Adapted Tags and Applied to Digital Library,” arXiv preprint arXiv:2312.08584, 2023.

[5] D. Rahman, M. Gupta, and K. Ahmed, “Deep Hybrid Learning for Library Recommendations,” J. Inf. Sci., vol. 49, no. 4, pp. 678–692, 2024.

[6] S. A. Anand and P. Rawat, “AI-Powered Information Accessibility and Personalization in Libraries,” IEEE Access, vol. 12, pp. 110932–110948, 2025.

[7] K. O’Reilly and M. Klein, “Conversational Agents in Libraries: Enhancing Engagement and Support through NLP,” Library Hi Tech, vol. 42, no. 1, pp. 99–117, 2024.

[8] N. Choudhury and H. Lee, “Multimodal AI Assistants for Accessibility in Digital Libraries,”

IEEE Trans. Access., vol. 13, pp. 18422–18439, 2025.

[9] M. Bagchi and A. Roy, "Generative AI-Based Metadata Modelling for Library Resource Discovery," arXiv preprint arXiv:2501.04008, 2025.

[10] A. Patel and R. Kumar, "Design of Conversational Agents for Library Information Systems Using NLP," Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 5, pp. 211–218, 2024.

[11] G. Zhou, W. Tian, R. Buyya, R. Xue, and L. Song, "Ethical Considerations and Fairness in AI Systems for Public Services," Artif.Intell.Rev., vol. 57, art.124, 2024.

[12] H. Lahza, "Adaptive Multi-Objective Resource Allocation for Digital Libraries," Modelling, vol. 5, no. 3, pp. 1298–1313, 2024.

[13] Y. Zhang, J. Kim, and L. Zhou, "User-Centered AI Recommenders for Academic Libraries," Inf. Process.Manage., vol. 60, no. 3, art. 103234, 2023.

[14] P. Yadav and N. Kumar, "Deep Graph-Based Recommendation Systems for Smart Libraries," Expert Syst. Appl., vol. 240, art.123650, 2025.

[15] S. Kayalvili, R. Senthilkumar, S. Yasotha, and R. S. Kamalakannan, "An Optimized Resource Allocation in Cloud Using Prediction-Enabled Reinforcement Learning," Scientific Reports, vol. 15, no. 1, 2025.

[16] R. Ahmed and P. Nair, "AI Integration in Library Systems: A Behavioral Perspective," Inf. Technol. Libr., vol. 43, no. 2, pp. 121–138, 2024.

[17] L. Tan and A. Gupta, "Artificial Intelligence Applications in Digital Library Systems: A Comprehensive Survey," IEEE Access, vol. 12, pp. 20231–20248, 2024.

[18] R. Ahmed and P. S. Nair, "AI-Enabled Library Management Systems for Metadata Automation," J. Inf. Technol. Serv., vol. 19, no. 1, pp. 66–79, 2023.

[19] Y. Wu, J. Liu, and H. Song, "AI-Driven Classification Models for Scalable Library Knowledge Organization," IEEE Trans. Learn. Technol., vol. 17, no. 3, pp. 211–226, 2024.

[20] D. Chowdhury and T. Leung, "Smart Libraries and Predictive Analytics: Transforming Library Operations with AI," Int. J. Libr. Inf. Sci., vol. 16, no. 4, pp. 189–202, 2024.

[21] D. Rahman, M. Gupta, and K. Ahmed, "Deep Hybrid Learning for Library Recommendations," J. Inf. Sci., vol. 49, no. 4, pp. 678–692, 2024.

[22] T. B. Furtado and A. Esmin, "Hybrid Content Dynamic Recommendation System Based in Adapted Tags and Applied to Digital Library," arXiv preprint arXiv:2312.08584, 2023.

[23] P. Yadav and N. Kumar, "Deep Graph-Based Recommendation Systems for Smart Libraries," Expert Syst. Appl., vol. 240, art.123650, 2025.

[24] C. Kaur, S. Verma, and D. Anand, "AI-Enhanced Recommendation in Academic Libraries Using User Behavior Analytics," J. Cloud Comput., vol. 13, no. 2, pp. 145–162, 2024.

[25] Y. Zhang, J. Kim, and L. Zhou, "User-Centered AI Recommenders for Academic Libraries," Inf. Process.Manage., vol. 60, no. 3, art. 103234, 2023.

[26] K. O'Reilly and M. Klein, "Conversational Agents in Libraries: Enhancing Accessibility and Engagement," Library Hi Tech, vol. 42, no. 1, pp. 99–117, 2024.

[27] N. Choudhury and H. Lee, "Multimodal AI Assistants for Accessibility in Digital Libraries," IEEE Trans. Access., vol. 13, pp. 18422–18439, 2025.

[28] A. Patel and R. Kumar, "Design of Conversational Agents for Library Information Systems Using NLP," Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 5, pp. 211–218, 2024.

[29] R. Salameh, "Artificial Intelligence for Accessibility in Libraries: A WCAG-Based

Evaluation," IFLA J., vol. 50, no. 1, pp. 25–39, 2024.

[30] Y. Liu, S. Chen, and L. Pan, "Inclusive AI Frameworks for Accessible Library Design," Comput. Human Behav., vol. 152, art. 108234, 2025.

[31] B.V.Srinivasulu "Fuzzy Logic-Driven Machine Learning Algorithms for Improved Early Disease Diagnosis " International Journal of Advanced Computer Science and Applications (IJACSA) - Volume 15 No 11 November 2024. Web of Science (Clarivate Q3 | JIF 0.7)

[32] B.V.Srinivasulu "Enhancing Healthcare Records Management With Efficient Graph Database Systems: A Novel approach" IJERST, ISSN 2319-5991, August, 2024(UGC CARE).

[33] Attended a International Conference on "ADAPTIVE FORGED PHISHING URL BY USING MACHINE LEARNING" ISBN: 979-8-3315-3884-2 by IEEE conference – ICSSAS - 2025 on from June 11th to June 13th, 2025.

[34] Attended a International Conference on " IMAGE LABELING USING CNN WITH WEB APPLICATION" ISBN: 979-8-3315-3884-2 by IEEE conference – ICSSAS - 2025 on from June 11th to June 13th, 2025.