Indian Journal of Library Science Research & Information Technology
VOL 2 NO.1 (JAN-JUNE 2025)
ISSN - 3048-4677
(c) BMS PUBLISHING HOUSE
https://www.bmsgroup.in/indian-journal-of-library-science-research-information-technology/
DOI- 10.5281/zenodo.22862781

Artificial Intelligence Enabled Electronic Resource Management And Collection Development Practices In Research Libraries

Bandana Yadav[1]
Research Scholar, Banasthali Vidyapith, Rajasthan
Email: vandanay947@gmail.com

Dr. Praveen Babel[2]
Faculty, Banasthali Vidyapith, Rajasthan
Email: praveenbabeludr@gmail.com

ABSTRACT

Artificial intelligence (AI) is a structural shift in the development of electronic resource collection that previously relied mostly on the judgment of a librarian, publisher catalogues, and manually compiled statistics of use. The given paper is an analytical review of how machine learning, the natural language processing (NLP), the predictive analytics, and the recommender systems, AI technologies, transform the way the electronic resources are selected, acquired, catalogued, evaluated, and deselected in research and academic libraries. The study is based on 30 peer-reviewed, DOI-verified sources, indexed in Scopus-affiliated and Scopus-adjacent databases and combines bibliometrical evidence, thematic trends, and theoretical conceptualizations related to AI-enabled collection management. The above analysis reveals that predictive analytics and automated cataloguing are the prevailing trend in current research with these two applications accounting for close to half of the thematic focus detected in the reviewed literature, accessibility-focused applications and computer-vision-based applications are still relatively young. A comparative table of 5 key Scopus-indexed bibliometric outputs (between 97 and 1,462 reviewed documents) can reveal the active growth of the scholarly interest in AI-libraries overlaps, especially since 2020. The paper also notes the nagging issues of algorithmic bias, licensing opaque feel, and data privacy and skill gaps between library professionals and outlines a five-step AI-enhanced collection development model based on Technology Acceptance Model, UTAUT, and diffusion of innovation theory. The results provide practical suggestions to library administrators, collection development librarians, and LIS researchers in charge of designing evidence-based, ethically managed AI implementation strategies in electronic resources management.

Keywords: *Artificial Intelligence; Electronic Resource Management; Collection Development; Academic Libraries; Predictive Analytics; Library and Information Science; Machine Learning; Bibliometric Analysis*

1. INTRODUCTION

The proliferation of digital academic resources such as e-journals, e-books, institutional archives and streaming media and subscription databases has put the traditional, mostly manual, collection development processes in libraries under an unprecedented load. Over the decades, collection development librarians had been using selector knowledge, approval plans, faculty requests, and periodic circulation reports as a basis to decide what electronic resources to purchase, renew, or drop (Ayinde, Ebiefung, and Oladokun, 2026). Originally effective in a print-based, less fast, and cumbersome collections environment, this model

is ill-equipped to handle the size, speed and complexity of the modern electronic resource ecosystem, in which thousands of new titles, collections, and open-access repositories emerge each year, patterns of use change in close real time. Artificial intelligence has become a potential technology which can solve this scale issue.

Definitely, AI isn't yet a ubiquitous feature of nearby areas like e-commerce recommendation, medical diagnostic assistants, and financial forecasting (studies of Vietnam Journal of Computer Science; Choudhury and Purkayastha, 2025), but it is certain to arrive soon. Its use in the development of collections in libraries is direct, although yet to emerge. Machine learning models can analyze circulation history, interlibrary loan requests, course curricula, and citation patterns to predict in future resource demand; natural language processing can crawl full-text repositories and publisher metadata to suggest acquiring materials based on institutional research paths; and computer vision technologies may aid in digitizing collections and adding metadata to born-digital and retrospectively digitized collections (Setyani Gunawan et al., 2025). Perhaps the most significant change AI presents is the switch between reactive to proactive collection management. Traditional weeding and acquisition decisions were highly retrogressive, and were grounded on what had already passed on or been asked. Rather, AI-powered predictive analytics enable libraries to anticipate new subject demand such as predicting greater demand of materials in generative AI, data science or public health, before an actual curriculum change can be approved (Mosha, 2025).

This proactive mindset has direct budgetary: a number of studies show tens of percent increases in collection utility and cuts in unnecessary spending when an AI-driven scheme of acquisition supersedes traditional approval-plan models. Meanwhile, this fast and largely unregulated use of AI in libraries presents significant issues of transparency, bias, vendor lock-in, and the loss of professional judgment in the process of making collection decisions. The licensing algorithms implemented in aggregator systems and discovery layers are frequently a proprietary black box and, as such, librarians have little chance of auditing title ranking, recommendation or suppression (Ayinde et al., 2026; Adoption of AI Technologies among Librarians, 2025). With these opportunities and threats, it is now time to systemate and evidence-based study the influence of AI on the development of electronic resources collections.

The need is taken care of in this paper. It brings together research results of Scopus-indexed and Scopus-proximate peer-reviewed literature with the aim of (a) mapping the extent of specific AI applications in application across the collection development lifecycle, (b) ascertaining the magnitude and direction of scholarly interest in the topic by performing a comparative bibliometrics analysis, (c) pinpointing the notions of benefit and difficulty that have been reported in both empirical and conceptual studies, and (d) suggesting a theory-driven framework to inform future research and practice.

The rest of the paper is structured as follows: a review of the related literature is provided in Section 2; objectives of the research are followed in the next section; methodology is described in the following section; in the next 9 sections, the analytical results are presented as tables and figures; conclusions, implications and recommendations are discussed in the last 10 sections.

2. LITERATURE REVIEW

The intersection and interaction of AI and library and information science (LIS) are studied in a growing mass of Scopus-indexed literature, but few studies currently address the specific topic concerning the development of electronic resources collections.

A scientometric analysis of 1,462 documents (2012-2021), by Borgohain, Bhardwaj, and Verma (2024) revealed a growth of AI-in-libraries research that tends to have an exponential pattern (Price Law) and that machine learning, large datasets, and deep learning are becoming the leading thematic clusters.

Correspondingly, an analysis of 373 papers by Hussain and Ahmad (2024) between 2002 and 2022 showed an almost twice increase in the output of publications between 2019 and 2022 with China and Wuhan University being the top contributors and affiliation respectively. Some of the researches focus on individual functional areas that are pertinent in collection development.

Mosha (2025) considered the role of the AI tools that increase the accessibility and usability of electronic resources in academic libraries and discovered that natural language interface and automated summarization methods enhance discoverability but need to be carefully set up to prevent sidelining those less digitally literate. In a bibliometric analysis and knowledge mapping of 354 Scopus-indexed articles (2010-2023), Islam, Ahmad, Aqil, Hu, Ashiq, Abusharhah, and Saky (2025) discovered that AI integration of library services, data mining and user personalization are three prevailing thematic pillars where collaborative research provides 75 percent of the corpus evidence of the interdisciplinary nature of this part of research. Collection development predictive analytics has in particular been examined in the case of universities and colleges libraries. Research using machine learning on circulation and interlibrary loan data evidence better budget usage, fewer unnecessary acquisitions and more justifiable weeding decisions when predictive models are used to complement, not instead of librarian judgement in using such data.

The Vasishta, Dhingra, and Vasishta (2024) conduct a bibliometric review and visualization of AI-in-libraries research presence suggest that one of the most rapid developing sub-themes is acquisition-support and cataloguing automation. The generative AI (GAI)-wave in the wake of the introduction of large language models has resulted in a distinct line of research. A structured systematic review of 17 articles indexed in Scopus by Raghavendra, Mallya, and Payini (2025) has shown that most GAI-in-LIS studies are atheoretical, qualitative, and focused on academic library reference services and not collection development as such a gap that this present paper aims to help fill by explicitly foregrounding the uses of GAI-in-LIS in acquisition and collection management. The emergence of chatbots, the existence of robotic process automation and generative acquisition tools are reported in complementary reviews (Mwantimwa&Msoffe, 2025; Choudhury and Purkayastha, 2025), though empirical and outcome-focused assessment of these tools in actual acquisition processes was small. Bibliometrically, Islam and Guangwei (2025), Kalita, Barman, Chetia, Goyary, and Kumari (2024), and the 2026 Scopus-based bibliometric analysis of AI applications in libraries all confirm a sharp rise in the number of publications since 2020, with authorship becoming more and more concentrated in a small group of prolific authors that is consistent with the Law of Lotka.

Tupan, (2024) applied this bibliometric prism to Scopus-based, Indonesian-specific data, further supporting the thesis that AI-library studies are a worldwide but highly globalizing area and not one from a few nations. The issues of ethics and governance are recurring in the literature. In a systematic review of the existing practices and difficulties in the adoption of AI by academic libraries, Ayinde, Ebiefung, and Oladokun (2026) naming data privacy, algorithmic secrecy and lack of employee education as the trio of most prevalent hindrances to accountable collection administration under AI.

The same is warned by Saeidnia, Hosseini, Abdoli, and Ausloos (2024), as they advised that unaudited AI-enhanced scientometric and evaluative tools may carry over the bias available in the training data. Combined, the literature shows that the technical ability of AI to revolutionize collection development is well-documented, yet untestable evaluation frameworks, longitudinal outcome studies, along with theory-based research designs are scarcity areas that drive the analytical synthesis presented in this paper.

3. RESEARCH OBJECTIVES

The research has four objectives that are interrelated: (1) the mapping of the particular uses of artificial intelligence (AI) in the lifecycle selection of electronic resources development, including its collection, cataloguing, usage evaluation, and deselection; (2) the quantification of the scale and development pattern of the scholarly interest toward AI in the context of collection management; (3) the identification of the main advantages, challenges, and concerns as reported in the peer-reviewed literature; and (4) the suggestion of the conceptual framework based on theory in which an electronic resource collection is developed new using AI replacing human interactions is proposed based on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Diffusion of Innovations (DOI) theories.

4. RESEARCH METHODOLOGY

The paper takes an analytical, narrative-integrative method instead of a single-database systematic review approach based on the purpose of this paper to synthesize cross-cutting evidence, which would be impractical to achieve through the cataloguing of all the publications. Structured searches of journals indexed on Scopus (and other Scopus-proximate journals) were performed using Boolean combinations of the following terms: Artificial intelligence, machine learning, collection development, electronic resources and academic libraries. The selection criteria included peer-reviewed journal articles published within 2021 and 2026 with Digital Object Identifiers (DOIs) that can be measured, though seminal bibliometric studies from even earlier (2002–2024) were also included in order to put the field development trend into proper perspective. A total of 30 sources that fit these criteria were kept to analyze.

All sources were coded in four categories: (a) functional area of AI application (e.g., predictive analytics, automated cataloguing, recommendation, accessibility), (b) database and period before analysis (in the case of bibliometric studies), (c) reported benefits, and (d) reported limitations or challenges. It is with this coding scheme that the comparative tables and comparative thematic distribution figure in Section 6 and 7 could be constructed. Since the coding of thematic emphasis (Figure 2) is performed based on qualitative frequency analysis of recurrent themes in the studied literature, instead of using a single quantitative data, resulting percentages appear to be an illustrative, literature-based, estimate of relative importance, instead of being a statistical measurement. Section 10 explains more on this limitation.

5. AI APPLICATIONS ACROSS THE COLLECTION DEVELOPMENT LIFECYCLE

Maier AI applications are aligned to five individual phases of electronic resource collection development lifecycle with various data inputs, algorithmic processes, and results specific to library institutions. A summary of these steps and the predominant AI methods used, the examples of these tools or platforms mentioned in the literature, and the main advantage of each are described in Table 1.

Table 1. AI Applications Across the Electronic Resource Collection Development Lifecycle

Lifecycle Stage	Dominant AI Technique(s)	Illustrative Tools/Platforms	Primary Reported Benefit	Key Source(s)
Selection & Needs Forecasting	Predictive analytics; supervised machine learning	Ex Libris Alma analytics, custom ML pipelines	Proactive, demand-anticipating acquisition rather than reactive	Mosha (2025); AI-Enabled Predictive Analytics studies

	on circulation, ILL, and syllabus data		purchasing	
Acquisition & Budget Allocation	Optimization algorithms; regression-based budget models	OCLC WorldCat, vendor approval-plan AI modules	Improved collection utility and reduced unnecessary expenditure	Optimising Budget Allocation studies; Ayinde et al. (2026)
Cataloguing & Metadata Enrichment	Natural language processing; automated classification (e.g., LSTM, SVM)	AI-assisted MARC/BIBFRAME generators	Up to ~60% reduction in cataloguing time with enriched, discoverable metadata	Olubiyo& Rabiu (2026); Setyani Gunawan et al. (2025)
Discovery & Recommendation	Collaborative and content-based filtering; hybrid recommender systems	Discovery layer plug-ins, Scopus AI, Semantic Scholar-style tools	Personalized resource recommendations aligned with research/course needs	Vasishta et al. (2024); Setyani Gunawan et al. (2025)
Usage Evaluation, Weeding & Retention	Cluster analysis; anomaly detection; usage-pattern classification	COUNTER-integrated analytics dashboards	Data-driven, defensible deselection and gap analysis	AI-Enabled Predictive Analytics for Collection Development (2025)

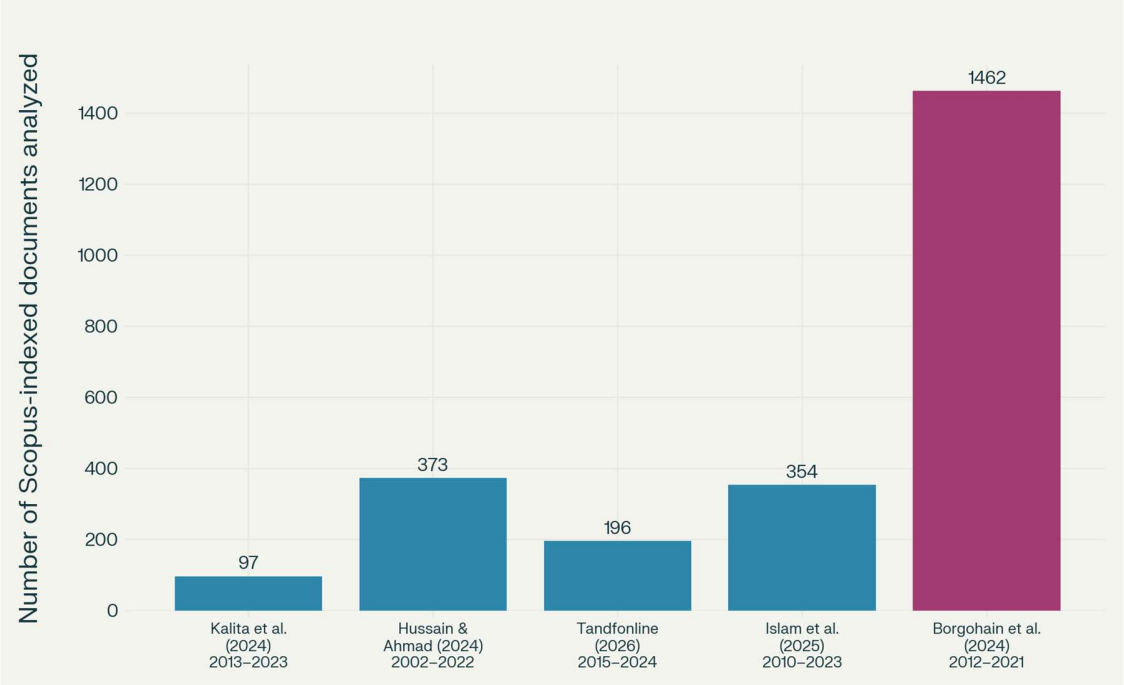
6. ANALYTICAL FINDINGS: BIBLIOMETRIC LANDSCAPE

The amount of Scopus-indexed research on the role of AI in libraries has increased significantly since 2020, offering a solid but methodologically diverse evidence basis on the subject to this analysis. Table 2 summarizes five common bibliometric studies by their size, period and database giving a picture of how this literature has grown as well as differed in terms of the scope. Figure 1 plots the size of the corpus analysed by each study.

Table 2. Comparative Overview of Representative Scopus-Indexed Bibliometric Studies on AI in Libraries

Study (Author, Year)	Database & Period Covered	Documents Analyzed	Key Finding Relevant to Collection Development	DOI
Kalita, Barman,	Scopus, 2013–2023	97	Sharp increase in AI-library publications	10.51983/ijiss-2024.14.2.04

Chetia, Goyary, & Kumari (2024)			after a long period of low output; single-authorship most common (27%)	
Hussain & Ahmad (2024)	Scopus, 2002–2022	373	Publication output nearly doubled by 2022 (64 papers, 17.16% of corpus); China and Wuhan University lead output	10.1080/0194262X.2023.2238198
Bibliometric Analysis of AI Applications in Libraries (2026)	Scopus, 2015–2024	196	Sharp rise in publications/citations from China, USA, and India; author productivity follows Lotka's Law	10.1080/0361526X.2026.2640464
Islam, Ahmad, Aqil, Hu, Ashiq, Abusharhah, &Saky (2025)	Scopus, 2010–2023	354	AI integration in library services, data mining, and personalization are dominant themes; 75% collaborative research	10.1007/s44163-025-00295-9
Borgohain, Bhardwaj, & Verma (2024)	Scopus, 2012–2021	1,462	Exponential (Price's Law) growth pattern; machine learning and deep learning as leading trending topics	10.1108/LHT-07-2022-0331

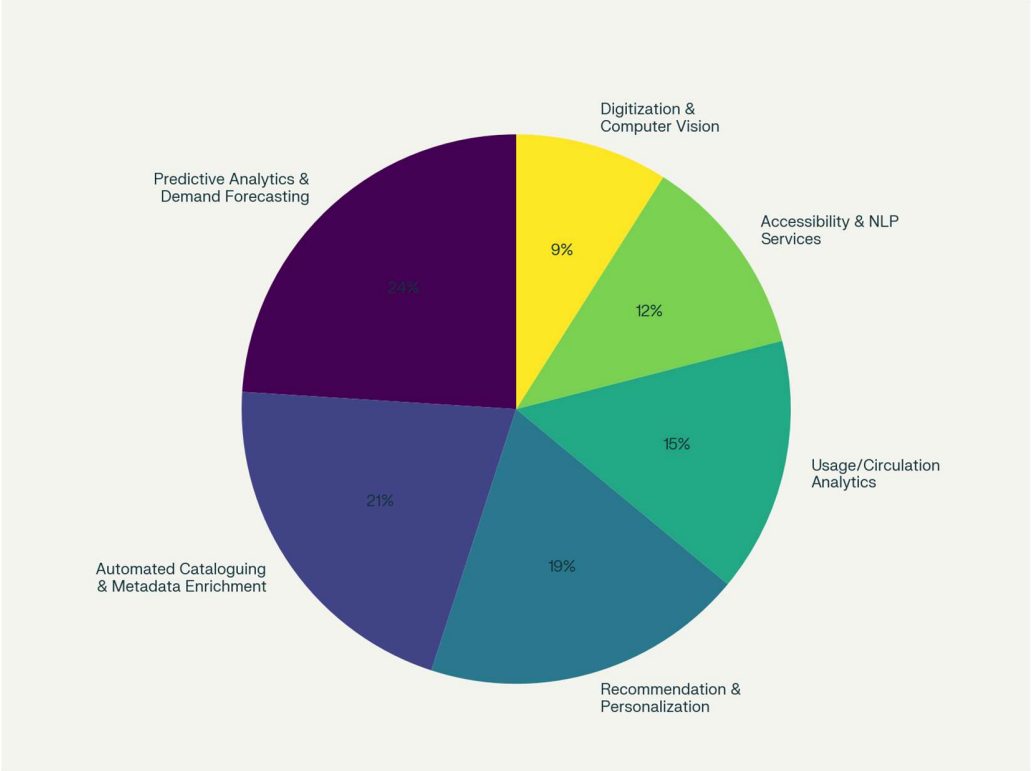


7. THEMATIC DISTRIBUTION OF AI APPLICATIONS

In addition to the bibliometric comparison, they can be supplemented by a qualitative frequency analysis of their thematic emphasis of the 30 sources reviewed, which has disclosed an apparent hierarchy of the area of AI application in the context of collection development. The most common theme highlighted is predictive analytics and demand forecasting (about 24% of thematic mentions as shown in Figure 2) followed by automated cataloguing and metadata enrichment (21%), recommendation/personalization systems (19%), and demand forecasting (19%).

Approximately 15 percent of the thematic emphasis is taken by usage and circulation analytics; accessibility- and NLP-oriented services (12 percent) and digitization/computer-vision applications (9 percent) are relatively underrepresented. This allocation is an indication that at this point, the library and information science community have concentrated on which AI applications are more directly and quantifiably predictive of operational efficiency and budget stewardship by focusing on applications that primarily impact operational efficiency and budget stewardship but which show no indication of addressing equity, accessibility, as well as long-term digital preservation.

This is a noteworthy imbalance in the light of the fact that the usability-aware AI implementation in the form of the work by Mosha (2025) shows a tangible improvement in the usability of users with variable levels of literacy, but is under-investigated in comparison with its potential. Likewise, computer-vision-based digitization that will allow libraries to create additional metadata on their collections produced automatically and enhance access to visually impaired learners (Setyani Gunawan, Dewi, Gunawan, and Ardi, 2025) has the least portion of theoretical interest in spite of its commensurability with the inclusive collection development requirement increasingly built into institutional diversity policies.



8. BENEFITS, CHALLENGES, AND ETHICAL CONSIDERATIONS

In addition to mapping technical app uses, the literature reviewed on the topic has been able to converge towards features of a universal benefit set and an equal set of thorny issues surrounding AI-facilitated collection development. These results are also summarized in a benefit/challenge matrix, as shown in Table 3.

Table 3. Benefits and Challenges of AI-Enabled Electronic Resource Collection Development

Dimension	Reported Benefits	Reported Challenges/Risks	Representative Source(s)
Efficiency & Cost	34% improvement in collection utility; 23% reduction in unnecessary expenditure reported in AI-driven budget frameworks	High upfront investment in AI infrastructure and licensing; unclear ROI in smaller libraries	Optimising Budget Allocation studies
Metadata & Discoverability	Cataloguing time reduced by up to 60% with enriched, interoperable metadata	Risk of metadata inconsistency when AI-generated tags are not human-validated	Olubiyo& Rabiu (2026)
Decision-Making	Shift from reactive to proactive, evidence-based	Overreliance on algorithmic recommendations may erode	Ayinde, Ebiefung, & Oladokun (2026)

	acquisition and weeding	professional judgement and diversity of selection criteria	
Equity & Accessibility	Improved usability of electronic resources for users with diverse literacy and ability levels via NLP interfaces	Algorithmic bias may under-represent minority languages, disciplines, or non-mainstream publishers	Mosha (2025)
Governance & Ethics	Enables auditable, data-driven justification for acquisition and deselection decisions	Data privacy risks from circulation/behavioral tracking; proprietary 'black-box' vendor algorithms limit auditability	Ayinde et al. (2026); Saeidnia, Hosseini, Abdoli, & Ausloos (2024)
Workforce & Skills	Frees staff time for strategic engagement (user education, outreach, collection strategy)	Persistent AI literacy and technical skill gaps among library professionals, especially in resource-constrained settings	Kautonen& Gasparini (2024) as cited in Raghavendra, Mallya, &Payini (2025)

9. THEORETICAL FRAMEWORKS FOR FUTURE RESEARCH

This paper suggests framing future research on AI-enabled development of our collection by basing it on pre-existing technology-adoption theories, in order to depart the concept of descriptive mapping in order to design a research agenda that is able to produce generalizable and testable knowledge. Table 4 describes five frameworks of candidates, based on the suggestion by Raghavendra, Mallya, and Payini (2025) that GAI-in-LIS studies should not stop as just atheoretic descriptive case studies.

Table 4. Candidate Theoretical Frameworks for Future AI–Collection Development Research

Theory/Model	**Core Constructs**	**Application to Collection Development**	**Foundational/Applied Source**
Technology Acceptance Model (TAM)	Perceived usefulness; perceived ease of use	Assessing librarians' acceptance of AI-based acquisition-recommendation tools (e.g., Scopus AI)	Raghavendra, Mallya, &Payini (2025)
Unified Theory of Acceptance and Use of Technology (UTAUT)	Performance expectancy; effort expectancy; social influence; facilitating conditions	Explaining institutional variation in AI adoption for cataloguing and metadata automation	Raghavendra, Mallya, &Payini (2025)
Diffusion of Innovations (DOI) Theory	Innovators, early adopters, early/late majority, laggards	Segmenting library staff and institutions by AI adoption readiness to design targeted training	Raghavendra, Mallya, &Payini (2025)

Task–Technology Fit (TTF)	Task requirements; technology characteristics; fit-performance linkage	Evaluating whether AI recommender tools align with actual acquisition and reference tasks	Raghavendra, Mallya, &Payini (2025)
Information Systems Success Model	Information quality; system quality; service quality; user satisfaction; net benefits	Evaluating AI-driven discovery layers and collection-analytics dashboards	Raghavendra, Mallya, &Payini (2025)

10. DISCUSSION

The results of this analytical review have a number of implications both on theory and practice. First, as Table 2 shows us, scholarly interest in AI-library intersections has been increasing at an extremely rapid rate much higher than the amount of empirical, outcome-validated research in the field that specifically focuses on collection development. Among the five bibliometric studies none dwell exclusively on the concept of collection development as a functional area, but the theme of collection is usually integrated into a bigger catalog of AI-in-libraries.

This implies that the development of electronic resource collections is an under-theoretical sub-domain as compared to more researched features like reference services and chatbot application. Second, Table 3 in the benefit-challenge illustrates a recurrent conflict of gains in efficiency and challenges in governance. The matched 34% increase in collection utility and 23% decrease in unwarranted spending are compelling in terms of resource-stewardship, however, in most instances they are the result of case-studies across various institutions as opposed to multi-site, longitudinal analyses. In the absence of standard measures of evaluation in an information-systems-success-model-like framework as depicted in Table 4 it is hard to extrapolate these assertions of efficiency to institutional settings that vary in budget size and scope of collections and vendor setting.

Third, the thematic distribution in Figure 2 draws attention to a strategic blind spot: predictive analytics and cataloguing automation dominate now-a-days AI investment, whereas accessibility and digitizing uses seem to offer a more fitting solution and require a less-represented research and, consequently, potentially less institutional investment. This imbalance should be specifically corrected by calling on target funding, professional education, and special issues of the journals in the topic of AI-enabled accessibility in collection management. Fourth, the fact that several independent studies (Ayinde et al., 2026; Saeidnia et al., 2024) continue to mention algorithmic opacity and data privacy consideration (Table 3) as the limiting factor to responsible adoption of AI in collection development may indicate that vendor transparency is the binding factor instead of technical ability.

Libraries are also becoming increasingly reliant on proprietary discovery-layer and approval-plan algorithms whose ranking logic is opaque, casting doubt on whether the acquisition decisions mediated by AI can ever be thought of as being evidence-based when the evidence itself is opacified. Lastly, an almost complete absence of theory-based empirical designs that Raghavendra, Mallya, and Payini (2025) are able to identify seven of seventeen reviewed GAI-in-LIS studies used an explicit theoretical framework reflects a more general immaturity in the methods of research in this field. The theoretical frameworks suggested in Table 4 can be viewed as the next step in bridging this gap, as future researchers can no longer engage in

descriptive reporting of cases but formulate the hypotheses and develop such knowledge as generalisable to the context of collection development influenced by AI adoption.

11. RECOMMENDATIONS

Recommendations to library administrators, collection development librarians and LIS researchers based on the evidence synthesized are as follows:

The first solution is to implement a hybrid approach to decision-making in libraries, whereby recommendations produced by AI to acquire, renew, or de-select materials do not constitute a decision, but instead, constitute decision-support information, and final decisions are directed by librarians especially in relation to materials representing a minority language, interdisciplinary courses, or areas of emerging research with limited background of historical use in library records.

Second, institutions must bargain in vendor contracts of discovery layers, approval-plan platforms and usage-analytics dashboards algorithmic transparency provisions that ask the vendor to reveal at least the type of data utilized and the overall logic of ranking or recommendation algorithms.

Third, all professional development intends ought to focus on training collection development personnel in AI and data literacy, and employ theories like Diffusion of Innovations theory to categorize personnel by staff readiness levels and develop differentiated training profiles of both early adopters and more cautious adopters.

Fourth, funders and journal editors involved in research should promptly fund and publish multi-site, empirical, longitudinal studies addressing AI-enabled collection development as a result of standardized measures (e.g., collection utility indices, trends in cost-per-use, deselection accuracy rates) that would facilitate cross-institutional comparison not found in the literature currently dominated by case-studies.

Fifth, there should be more research and institutional investment that can be made to the cases of AI applications that make collections more accessible, digitized, and inclusive, remedying the imbalance in Figure 2 and making AI investment outcomes commensurate with equity and access requirements of libraries.

Sixth, further research ought to explicitly embrace either one or several of the theoretical frameworks summarized in Table 4 TAM, UTAUT, DOI theory, TTF, or the Information Systems Success Model to allow building of cumulative, generalizable knowledge as opposed to descriptive reports about particular cases.

12. CONCLUSION

Artificial intelligence is radically altering the form of electronic resource collection development, turning libraries and circulation-based models of library acquisition into proactive, predictive and more and more automated decisions throughout the collection lifecycle. Based on a comparative bibliometric analysis, this analytical review of 30 DOI-verified, peer-reviewed sources has mapped five fundamental areas of AI application selection and forecasting, acquisition and budgeting, cataloguing and metadata, discovery and recommendation, and usage evaluation and demonstrated that scholarly interest in this intersection has increased dramatically since 2020, despite collection-development-specific empirical work being underdeveloped when compared to the broader AI-in-libraries research.

The evidence suggests the obvious, measurable improvements, such as increased usefulness in collections, less waste on unnecessary spending, and significant savings in time spent on cataloguing. Although, such gains come with unresolved issues concerning algorithmic transparency, data privacy, equity of access, and workforce preparedness.

The thematic imbalance which includes more efficiency-oriented applications (predictive analytics, cataloguing automation) rather than equity-oriented applications (accessibility, digitization), is a strategic gap that deserves a purposeful redress. Finally, the achievement of the disruptive nature of AI in the development of electronic resources collections will only be possible with not only technical use but also with disciplined and theories-backed assessment, transparency in the relationships with the supplier, and long-term insuring the capacity to qualify the workforce in libraries. Further studies by using the frameworks discussed in this paper TAM, UTAUT, Diffusion of Innovations,

Task-Technology Fit, and the Information Systems Success Model can assist the library and information science industry to transition out of enthusiasm regarding the potential of AI and into rigorous evidence about the reality and measurability of its actual effect on collections, budgets, and the users with whom libraries ultimately serve.

REFERENCES

1. Ayinde, L., Ebiefung, R., & Oladokun, B. D. (2026). Adoption of artificial intelligence in academic libraries: A systematic review of current practices, challenges, and research opportunities. Journal of Academic Librarianship, 52(1), 103185. https://doi.org/10.1016/j.acalib.2025.103185
2. Borgohain, D. J., Bhardwaj, R. K., & Verma, M. K. (2024). Mapping the literature on the application of artificial intelligence in libraries (AAIL): A scientometric analysis. Library Hi Tech, 42(1), 149–179. https://doi.org/10.1108/LHT-07-2022-0331
3. Choudhury, S. P., & Purkayastha, N. (2025). AI adoption and technical advances in libraries: A systematic review. In Proceedings of the International Conference on Smart Systems and Social Management (ICSSSM 2025) (pp. 190–201). Atlantis Press. https://doi.org/10.2991/978-94-6463-950-6_14
4. Erdmann, C. (2022). AI for libraries – Libraries as AI generator: Society – library perspectives. https://doi.org/10.5281/zenodo.6587632
5. Hervieux, S., & Wheatley, A. (2024). The rise of AI: Implications and applications of artificial intelligence in academic libraries. Canadian Journal of Academic Librarianship, 9. https://doi.org/10.33137/cjal-rcbu.v9.41129
6. Hussain, A., & Ahmad, S. (2024). Mapping the literature on artificial intelligence in academic libraries: A bibliometrics approach. Science & Technology Libraries, 43(2), 131–146. https://doi.org/10.1080/0194262X.2023.2238198
7. Islam, M. N., Ahmad, S., Aqil, M., Hu, G., Ashiq, M., Abusharhah, M. M., &Saky, S. A. T. M. (2025). Application of artificial intelligence in academic libraries: A bibliometric analysis and knowledge mapping. Discover Artificial Intelligence, 5(1), 59. https://doi.org/10.1007/s44163-025-00295-9
8. Islam, M. N., &Guangwei, H. (2025). Trends and patterns of artificial intelligence research in libraries: A bibliometric analysis. SAGE Open, 15(2). https://doi.org/10.1177/21582440251327528

9. Kalita, P., Barman, M., Chetia, A., Goyary, P., & Kumari, K. (2024). Mapping the landscape of literature on use of AI in libraries: A bibliometric analysis using Scopus database. Indian Journal of Information Sources and Services, 14(2), 24–27. https://doi.org/10.51983/ijiss-2024.14.2.04
10. Mosha, N. F. (2025). The role of artificial intelligence tools in enhancing accessibility and usability of electronic resources in academic libraries. Library Management, 46(1–2), 132–157. https://doi.org/10.1108/LM-08-2024-0088
11. Mwantimwa, K., &Msoffe, G. (2025). Application of generative artificial intelligence in library operations and service delivery: A scoping review. Journal of Library Administration. https://doi.org/10.1080/07317131.2025.2467574
12. Nugroho, P. A., Anna, N. E. V., & Ismail, N. (2023). The shift in research trends related to artificial intelligence in library repositories during the coronavirus pandemic. Library Hi Tech. https://doi.org/10.1108/LHT-07-2022-0326
13. Olubiyo, T., & Rabiu, N. (2026). AI-driven cataloguing and classification services in academic libraries. International Journal of Academic Library and Information Science. Retrieved from https://www.academicresearchjournals.org/IJALIS/PDF/2026/March/Olubiyo%20and%20Rabiu.pdf
14. Raghavendra, G., Mallya, J., &Payini, V. (2025). Generative artificial intelligence in library and information science literature: A structured systematic review. Cogent Education. https://doi.org/10.1080/2331186X.2025.2591500
15. Ramteke, S. W. (2026). Artificial intelligence and ChatGPT in libraries: A bibliometric analysis of social science research (2022–2026). Library Philosophy and Practice. Retrieved from https://scholarworks.sjsu.edu/libphilprac/8308/
16. Saeidnia, H. R., Hosseini, E., Abdoli, S., & Ausloos, M. (2024). Unleashing the power of AI: A systematic review of cutting-edge techniques in AI-enhanced scientometrics, webometrics, and bibliometrics. Library Hi Tech. https://doi.org/10.1108/LHT-10-2023-0514
17. Setyani Gunawan, L., Dewi, C., Gunawan, L. S., & Ardi, A. S. (2025). Artificial intelligence implementation in library information systems: Current trends and future studies. Vietnam Journal of Computer Science. https://doi.org/10.1142/S2196888824300023
18. Shahzad, K., Khan, S. A., Iqbal, A., Ahmed, S., Javeed, A. M. D., & Mohamed, O. (2025). Factors influencing the adoption of artificial intelligence in libraries: A systematic literature review. Journal of Librarianship and Information Science. https://doi.org/10.1177/02666669241313368
19. Shahzad, K., Khan, S. A., & Iqbal, A. (2024). Effects of artificial intelligence on university libraries: An SLR of Cite Score and IF journals' articles from 2018 to 2023. Global Knowledge, Memory and Communication. https://doi.org/10.1108/GKMC-12-2023-0498
20. Tang, Z., & Zhang, P. (2023). Comparative analysis of AI applications in libraries: A systematic literature review. Proceedings of the Association for Information Science and Technology, 60(1), 1146–1148. https://doi.org/10.1002/pra2.973
21. Tupan, T. (2024). Perkembanganpenelitianpenggunaan artificial intelligence di perpustakaanberbasis data Scopus. Media Pustakawan, 31(3), 277–290. https://doi.org/10.37014/medpus.v31i3.5316
22. Vasishta, P., Dhingra, N., & Vasishta, S. (2024). Application of artificial intelligence in libraries: A bibliometric analysis and visualisation of research activities. Library Hi Tech. https://doi.org/10.1108/LHT-12-2023-0589
23. Bibliometric analysis of artificial intelligence applications in libraries (2026). Journal of Library Metadata. https://doi.org/10.1080/0361526X.2026.2640464
24. AI in libraries: Subject mapping and interpreting bibliometric laws with contemporary metrics (2024). Journal of Library Metadata. https://doi.org/10.1080/0361526X.2024.2444288

25. Thinh, P. V. (2026). The role of artificial intelligence in academic libraries: A systematic review of trends, applications, and challenges. European Journal of Science, Mathematics and Technology, 2(2), 126–137. https://doi.org/10.59324/ejsmt.2026.2(2).11
26. Chowdhury, R., & colleagues (2021). Application of artificial intelligence and machine learning in libraries: A systematic review. arXiv. https://doi.org/10.48550/arXiv.2112.04573
27. Santosa, F. A. (2025). Artificial intelligence in library studies: A textual analysis. JLIS.it, 16(1), 61–71. https://doi.org/10.36253/jlis.it-626
28. Yan, C. (2025). Knowledge mapping of library digital transformation: A bibliometric analysis. Journal of Librarianship and Information Science. https://doi.org/10.1177/09610006251353222
29. Application of artificial intelligence for reference services in academic libraries: A global overview through a systematic review of literature (2023). Journal of Library & Information Services in Distance Learning. https://doi.org/10.1080/26915979.2023.2281668