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Future Trends in AI and ML Applications for Library Collection Development: A Roadmap

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A B S T R A C T

The fast growth of academic material, limited library budgets, and changing user needs have made it even more important to develop new ways to build library collections. This study aims to look at how Artificial Intelligence (AI) and Machine Learning (ML) are being used now and in the future in academic and research libraries. The study will look for trends that might change how libraries work, technologies that make these changes possible, and ethical issues that need to be considered. This paper reviewed academic publications, case studies, and technical reports published between 2014 and 2025. These articles came from Scopus, Web of Science, and Google Scholar.

The key findings show that AI and ML technologies are being used successfully for things like predicting demand, performing automated reviews, doing predictive analytics, helping with decisions, automating acquisitions, and giving personalised service to customers. These technologies make collection development procedures more scalable, accurate, and responsive. However, using them comes with many ethical problems, such as algorithmic bias, a lack of transparency, data privacy threats, and the possibility that curation would lose its human touch. The study concludes that AI/ML may significantly enhance the process of developing collections. Still, libraries must use them carefully to make sure that people are in charge, that everyone has the same access, and that they are responsible. A strategic roadmap is suggested to help with the responsible use of AI technology. It stresses ethical governance, phased experimentation, and participatory design.

This study presents practical implications for library professionals, administrators, and policy-makers aiming to improve their collections while protecting the essential ideals of librarianship.

Keywords: Artificial Intelligence, Machine Learning, Collection Development, Academic Libraries, Research Libraries, Forecasting, Predictive Analytics, Automated Reviews, Decision Support Systems, Personalisation, Bias in AI Systems, Algorithmic Accountability

Introduction

Artificial intelligence (AI) and machine learning (ML) are becoming more widespread across several sectors, including libraries and information centres. AI and ML technologies may facilitate the automation of repetitive processes, like cataloguing and indexing, while enhancing the efficiency and accuracy of information retrieval and management services.[1] Libraries serve as guardians of historical and cultural information, and preserving delicate or decaying items is an essential duty. Artificial intelligence-driven technologies are used to digitise, repair, and preserve documents, photographs, and other artefacts. Utilising sophisticated picture identification and restoration methods, AI guarantees the preservation of even the most fragile objects in digital formats, therefore protecting them for future generations. Artificial intelligence is crucial in addressing disinformation and validating sources in the digital era. Libraries, as reliable information centres, may use AI algorithms to assess the reliability of internet material, identifying possibly erroneous or misleading information.

These technologies assist librarians in selecting trustworthy digital resources and promoting critical thinking and informed decision-making among users. By incorporating AI-driven fact-checking technologies into their services, libraries reinforce their role as guardians of truth in a more intricate information environment. Another notable effect of AI in libraries is its capacity to promote multidisciplinary study. AI systems can analyse extensive datasets across several disciplines, uncovering correlations and patterns that may not be readily discernible to human researchers. By providing these features, libraries may facilitate collaborative research endeavours, allowing researchers from many disciplines to collaborate in addressing intricate issues. AI-driven discovery systems facilitate spontaneous learning by recommending relevant subjects or resources a user may not have previously considered. Libraries are adopting AI to increase operational efficiency. Chatbots and virtual assistants are used to answer basic requests, allowing librarians to concentrate on more sophisticated responsibilities. These AI systems provide 24/7 support, guaranteeing that consumers may get assistance at any time. Furthermore, ML algorithms can forecast and simplify procedures like book returns and interlibrary loans, lowering wait times and improving the user experience. Users of digital libraries in the twenty-first century typically want the flexibility to access these materials independently.[2]

In addition, academic and research libraries are facing tremendous pressure to provide comprehensive and relevant collections amidst flat or declining budgets, increasing publication outputs, rising material costs, and changing user behaviours and expectations.[3-5] Historically, expert librarians shouldered the labour-intensive process of manual collection development using their specialised knowledge, contextual insights, and evaluative skills to predict community needs and curate high-quality, balanced collections.[6,7] However, Relying solely on human efforts is becoming increasingly impractical given the volume of published material today, estimated at over 2.5 million articles per year in English-language STM (scientific, technical, and medical) journals alone.[8] Although collection budgets have been strained to keep pace,[9] this output steadily rises year after year.[10] As a result, libraries cannot acquire even a fraction of relevant material for their communities, heightening concerns over increasing gaps in collections.[11,12]

At the same time, there is growing recognition across academia that library collections significantly impact scholarly productivity and research advancement.[13-15] Indeed, researchers confirm that access gaps created by libraries' inability to provide complete collections corresponding to faculty output can slow scientific progress.[16,17] Students likewise report problems finding sufficient material in library collections to meet their academic needs, negatively impacting learning outcomes and satisfaction.[18] Expanding online availability has helped mitigate access issues for some disciplines in the sciences and medicine. However, gaps persist in book-focused disciplines and those reliant on newer formats like media, data, software, and even micro publications.[19,20]

Clearly, new strategies and solutions are urgently required for libraries to manage the quantity of published material and satisfy growing expectations for immediate desktop delivery in today's digital environment.[21] Recent exponential gains in computing power coupled with advances in data mining, machine learning (ML), and artificial intelligence (AI) techniques offer promising new opportunities for libraries to optimise collections in innovative ways.[22-24] By exploiting automated methods to uncover hidden patterns and insights, AI systems can help address key collection development challenges related to the information deluge. As algorithms and applications mature, AI/ML software has significant potential to complement (or perhaps someday partially replace) subjective human selection. These technologies open up possibilities to work at scales beyond human capacity, enabling more evidence-based, granular, and dynamic collection analysis than previously feasible.[25,26] This paper explores emerging and anticipated AI/ML applications that could enhance collection development workflows for academic and research libraries over the coming decade. It reviews state-of-the-art implementations that are already assisting practitioners with evaluative tasks and predictive analytics. Expected near-future capabilities are also considered, along with a candid examination of persisting limitations and critical ethical impacts of introducing automation. Finally, a proposed roadmap and recommendations guide interested library leaders.

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in setting strategic priorities to deliberately yet judiciously begin leveraging AI innovations to optimise collections amidst increasingly complex constraints.

AL/ML Trends

Figure 1[27] shows the main AI trends and developments in artificial intelligence and machine learning projected to be dominant in 2025.

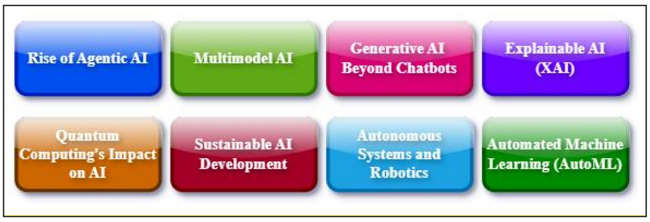

Figure 1.AI and Machine Learning Trends

Rise of Agentic AI

Agentic AI represents a significant advancement in artificial intelligence, defined by systems that execute tasks autonomously with little human supervision. This idea is gaining momentum as organisations aim to improve productivity and efficiency via autonomous agents that can perform complicated tasks independently. This implies that these technologies will undergo metamorphosis to aid and autonomously manage duties and decision-making processes inside the workplace.

Multimodal AI

Multimodal AI is expected to evolve significantly, allowing systems to accept and incorporate input from various sources, including text, pictures, and voice. Finally, this application will give users new meanings, allowing programs to respond more naturally to rich multisource input. For example, customer care chatbots that can comprehend text and visual inputs would be able to deliver much more efficient and accurate assistance. This is particularly important in many fields, such as health, where several kinds of data may lead to more precise diagnoses and insights.

Generative AI Beyond Chatbots

Generative AI is expanding beyond standard chatbot applications as organisations look for new methods to use large language models (LLMs). Unstructured data and multimedia content

Creation is becoming more important. This progression tackles the scale challenges associated with previous generative AI implementations, making these technologies more useful in various sectors.

Explainable AI (XAI)

The requirement for openness and interpretability grows in tandem with the complexity of AI systems. XAI, or explainable AI, is a method of making an AI system's judgements understandable to people, which is critical in building confidence in automated systems. Such a tendency will be increasingly prevalent in industries such as banking and healthcare, where understanding the reasoning behind a choice might be crucial.

Quantum Computing's Impact on AI

Quantum computing relates to the area of artificial intelligence, providing extraordinary computational capacity that may be utilised to speed up data processing and model training. These quantum technologies will soon be widely accessible, and organisations that use AI solutions that use quantum power will have a competitive edge in handling complex challenges in a variety of disciplines, including medicine development and logistics optimisation.

Sustainable AI Development

As sustainability becomes a trend, AI development approaches are being affected. Green AI is a well-known concept that describes how organisations are increasingly focusing on reducing the environmental footprints of data centres and machine learning operations. Initiatives include harnessing renewable energy and optimising resource utilisation in AI processes, thus balancing technology growth with environmental responsibility.

Autonomous systems and robots

Autonomous technologies, such as robots and drones, will be widely used in 2025 to complete tasks traditionally performed by people in industries such as logistics, healthcare, and manufacturing. Integrating AI into robots will improve their capabilities, allowing them to do complicated tasks autonomously.

Automatic Machine Learning (AutoML)

AutoML technologies streamline the machine learning process by automating important phases such as data preparation and model selection. This trend enables organisations that lack considerable technical skills to more easily install machine learning solutions, democratising access to sophisticated analytics capabilities.

Objectives and Methodology Objectives:

The main objective of this study is to present an up-to-date and thorough assessment of AI and machine learning applications in research and academic library collection creation. Specific objectives include:

- Identifying key trends and applications of AI/ML in library workflows.
- Addressing ethical concerns and adopting responsible AI systems.
- Providing a roadmap for integrating AI tools with institutional priorities.

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Methodology

This study uses academic publications, conference proceedings, case studies, and industry reports that were published between 2014 and 2025. Scopus, Web of Science, and Google Scholar are some of the places where data comes from. Some of the keywords that were used were "AI in libraries," "machine learning for collection development," "predictive library analytics," and "AI ethics in public institutions." The criteria for selection were based on how relevant the material was to academic or research libraries, how well it had been utilised in practice, and how well it might be used strategically. We looked at the materials to ensure they were quality, up-to-date, and useful.

Literature Review

Artificial intelligence can enhance several facets of academic library services in India, including technical areas, indexing, acquisition procedures, natural language processing (NLP), pattern recognition, and the integration of robots. The study[28] intended to synthesise empirical works on the use of artificial intelligence and machine learning in libraries. Data was gathered from many databases, including Web of Science, Scopus, LISA, and LISTA. Thirty-two publications were found and analysed, demonstrating that contemporary AI and ML research is mostly theoretical, with some academics emphasising implementation projects or case studies. Logistic regression, KNN, AdaBoost, recommender systems, SVM, and association rules are popular techniques for collection management, circulation, and internal activities. Advanced AI and ML methods, such as pattern recognition and MAS, are also utilised to secure and manage libraries.

Provided an overview of how artificial intelligence (AI) is used in library services, including applications such as expert systems in reference services, technical indexing, acquisition, natural language processing, pattern recognition, and robotics. Cataloguing, user recommendations, and data analysis. This also investigates the possible advantages and problems of incorporating AI into library services, as well as future research goals in this area.[29]

According to,[30] the significance of artificial intelligence (AI) in commercial and scientific applications is rapidly escalating. Artificial intelligence is used to enhance goods, forecast consumer behaviour, monitor inventories, and analyse extensive data sets. Artificial intelligence agents are used to enhance the efficacy of search engines and cellphones. AI is being evaluated for many uses in libraries, particularly in data analysis, facilitating remote access to library services, and establishing the library as a hub for research using Big Data. Artificial intelligence may execute mundane operations now necessitating human intervention, therefore allowing librarians to provide the specialised knowledge necessary for advanced research.

Indicates that academic libraries need to adopt AI integration, dedicate resources for staff training to guarantee proficiency in successful AI utilisation, and institutionalise AI integration as a normative practice across all library divisions. The report further advises that budgetary allocations include the expenses associated with AI. The incorporation of AI may facilitate the identification of items in Indian academic libraries, enhancing resource allocation efficiency and effectiveness. The study's results highlight the significance of AI in improving library functions and allocation of resources.[31]

Investigated the use of Artificial Intelligence (AI) in library collection creation and administration, emphasising machine learning, predictive analytics, and automation. It underscores the advantages of AI, like economic efficiency and enhanced user engagement, while also addressing ethical issues such as data privacy and algorithmic prejudice. The research proposes a comprehensive framework for the integration of AI in libraries to facilitate the successful utilisation of AI applications, while simultaneously resolving pertinent challenges and enhancing overall library management practices.[32]

This study[33] examined the significant influence of AI on libraries, highlighting its crucial role in transforming information access, administration, and dissemination. AI-driven tools and apps enable libraries to enhance operational efficiency, customise user experiences, and foresee the changing demands of users. AI enables librarians to enhance data analytics, optimise operations, and provide tailored help, signalling a new age of innovation in library services. Despite encountering hurdles like ethical dilemmas and budget limitations, the judicious use of AI has the potential to advance libraries into a future characterised by dynamic and inclusive information distribution.

Explored future trends and ramifications of open-source artificial intelligence (AI) for libraries, emphasising technical progress, enduring effects, and the changing responsibilities of librarians. Significant developments include natural language processing, sophisticated recommendation systems, and enhanced data analytics, anticipated to augment user experience and operational effectiveness. These technologies will facilitate personalised service delivery, optimise operations, and transform library personnel responsibilities. Librarians must cultivate new competencies and champion the ethical use of AI, ensuring that AI applications correspond with the library's principles of inclusiveness and accessibility.[34]

Examined the application of AI in libraries, emphasising cataloguing, categorisation, information retrieval, virtual reference services, and personalised user experiences. It emphasises the potential benefits of machine learning, natural language processing, and chatbots for increasing productivity and customer happiness. However, concerns

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about data privacy, prejudice, and technical accessibility must be addressed. The research presents a complete overview of AI's revolutionary role in libraries and proposes long-term implementation solutions.

Investigated the incorporation of artificial intelligence and machine learning into library management systems, emphasising its transformational effects on resource management, user services, and operations. It underscores the efficacy of activities such as cataloguing, information retrieval, personalised suggestions, and chatbot interactions. Notwithstanding obstacles such as employee opposition, substantial initial expenditures, and data privacy issues, the article posits that the sustained use of AI and machine learning may result in more efficient, personalised, and user-centric library services.[34]

Review of AI/ML Applications in Collection Development

Collection development incorporates interrelated activities to continually build, maintain, and evaluate library holdings serving designated communities[37,38] Key tasks include anticipating user needs, identifying relevant materials, comparing purchase options, deciding what to acquire immediately and what to defer, deselecting outdated or superseded items, shaping an overall collection composition aligned to institutional priorities, and evaluating performance.[39] AI/ML applications are emerging to assist with many of these functions, as summarized in Table 1 and detailed in subsequent sections.

Table 1.AI/ML Application Areas in the Literature Review

Study Summary	AI/ML Technologies	Application Areas
Synthesized 32 empirical studies on AI/ML use in libraries.[28]	Logistic Regression, KNN, AdaBoost, SVM, Recommenders	Collection management, circulation, internal workflows
Overview of AI in library services (reference, cataloguing, NLP, robotics).[29]	Expert Systems, NLP, Pattern Recognition	Cataloguing, indexing, acquisition, user recommendations, technical processing
Focus on AI in commercial/scientific data handling and remote access services.[30]	AI Agents, Predictive Analytics	Search enhancement, data analysis, remote service support
Emphasizes institutional AI integration and staff readiness.[31]	AI for automation and allocation	Resource identification, staff training, policy- level integration
AI in collection creation with focus on machine learning and ethics.[32]	ML, Predictive Analytics, Automation	Economic optimization, user engagement, ethical resource management
Reviews how AI transforms access, customization, and operations in libraries.[33]	AI Tools & Apps, Data Analytics	Personalized services, operational efficiency, predictive service models
Highlights open-source AI trends and evolving librarian roles.[34]	NLP, Recommender Systems	Personalized delivery, data-driven operations, upskilling librarians
Discusses AI in cataloguing, information retrieval, and virtual reference services.[35]	ML, NLP, Chatbots	Metadata generation, virtual support, personalized UX
Covers AI in library management systems and resource operations.[36]	Chatbots, ML, Recommenders	Personalized suggestions, cataloguing, operations optimization, user engagement

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Demand Forecasting

A perennial challenge for selectors is anticipating future demand for materials since user needs continuously evolve. Librarians traditionally consult past circulation and inter-library loan records to inform decisions about acquiring more items on certain topics. However, these reactive indicators reveal little about interest levels for new or obscure subjects lacking existing coverage.[40,41] Consequently, gaps persist in niche research areas and emerging disciplines despite potential unmet needs.[42] AI techniques like machine learning offer more scalable, nuanced approaches to demand forecasting by detecting non-obvious patterns across datasets. Federated library networks have cooperated on early initiatives to aggregate anonymised usage logs allowing comparisons across thousands of patrons and titles for predictive modelling experiments.[43-45]

Researchers at the University of Magdeburg, for example, developed methods to score publication similarity by modelling subject keywords/classifications, referenced sources, and abstract terms using ML classifiers.[46] By linking usage to properties of widely held titles, their system can infer potential relevance for new books based on comparable attributes. Testing against human expert ranking on 150 computer science publications found ~70% agreement with algorithmic predictions. The authors propose selecting new acquisitions aligned to areas of high interest by extrapolating from observed readership behaviour. This demand-driven approach also provides data to inform tough cancellation decisions by identifying predictably low-use items.

A team from Rutgers University similarly analysed aggregated usage logs combined with MARC cataloguing records to train ML algorithms but focused specifically on predicting long-term preservation value.[47] Items rarely used in the past but sharing other characteristics with more frequently used titles were tagged as having uncertain archive value. On the other hand, highly used periodicals considered similar to those with enduring readership are considered to have greater value and should be protected and preserved. This analytical approach changes the policies of retention away from a sole reliance on usage statistics to also look at comparable assets that are still gaining readership into the future.

As exciting as demand forecasting applications look, platforms training algorithms on past activity inherently favour the status quo rather than discovering latent needs or revealing structural biases that discourage marginalised groups from interacting with library systems.[48] This chapter discusses ethical risks of perpetuating exclusion further in Section 4. However, thoughtfully designed models that account for such limitations could potentially help selectors to anticipate relevant acquisitions—especially for the proliferating topics that are interdisciplinary and not very well covered by current methods or metrics.

Automated Reviews

Selecting quality content aligned to curricular and research priorities requires thoroughly reviewing numerous options for potential purchase. Publication details like scope, intended audience, author credentials, publisher reputation, writing quality, currency, accuracy, and more guide decisions about overall suitability and projected local value. Traditionally, this labour-intensive process depends on subject specialists manually reviewing book descriptions, tables of contents, sample text, reviews, and more.[49] AI applications are emerging to assist by automatically summarising key details about new items to inform eligibility assessments by librarians.

Software company ProQuest recently developed Intelligent Content Review, employing natural language processing (NLP) techniques to extract concepts from samples of academic book content.[50] The automated analysis checks writing quality, determines target audience, identifies instructional components for textbooks, and estimates currency based on cited references. These algorithmically derived details on over 20 validation points are displayed through an online management interface to help selectors efficiently evaluate large title lists by focusing their efforts only on high-potential matches. Customised to institutional needs and priorities, such tools could drastically increase review capacities compared to manual methods.

Elsevier has also introduced AI functionality into its Pure workflow manager used by institutional managers and librarians to evaluate faculty research output for consideration.[51] The system can now automatically generate concise text summaries of publications to facilitate selection decisions. This text extraction assists reviewers in quickly assessing relevance or new contributions for numerous submissions without needing to retrieve and skim full documents. Especially when embargos on publisher access can delay access to just-in-time overview information supporting more timely and better-informed decisions, higher-quality summaries more aligned with the needs of users and capable of maturity from NLP could minimise access requirements while improving effectiveness over manually skimming everything possible if AI assistance based on generated descriptions only were used in content selection.

Despite promising productivity gains, risks of perpetuating or even amplifying biases are again a concern with automated review systems trained on narrow, homogeneous inputs. All selection decisions include inherent subjectivities[52] which AI currently struggles to acknowledge due to dataset limitations.[53] Ethical considerations around accountable and

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transparent AI/ML development,[54] especially for public institutions, are covered further in Section 4.

Decision Support

Even with support summarising options, selectors still face complex allocation decisions about what specifically to acquire given limited budgets. Various commercial library platforms now incorporate AI-assisted analytics with automated alerts and notifications to guide ongoing decisions.[55] ProQuest again provides an illustrative example via its OASIS management system, which monitors selection lists and newly available titles against individual library criteria and objectives encoded into reusable collection development policies.[56] Publication details get algorithmically compared to customised institutional priorities, real-time availability, and pricing data to generate notifications highlighting strongest matches. Machine learning trains the system's recommendations by responding to librarian feedback indicating which notifications led to actual orders versus rejects.

Ex Libris recently unveiled a similar workflow enhancement for its Alma platform using AI to filter new title notifications by comparing encoded local collection policies against aggregated analytics on each book's subject similarity to the institution's catalogue strength or weaknesses.

Librarians determine areas that need stronger collections and those that are sufficiently developed to provide the foundation for automated determination of titles appropriate for purchase. Tailored recommendations, therefore, closely match measurable areas for improvement. The system also learns from responses to further hone its selection notices. Decision support systems are not yet able to fully automate selections, but they do illustrate how AI/ML techniques can exploit detailed analytics to make recommendations far better aligned with institutional collection strategies than relying exclusively on new publication notifications or best-seller lists.[57]

Dynamic retraining workflows also support the maintenance of recommendations that remain responsive to local needs as offerings and community needs constantly shift. However, limitations still exist in accounting for regional diversity in research, emphasising that static classification schemes fail to capture it well. Section 4 discusses ethical issues and transparency requirements for AI-based decisions before addressing even greater levels of automation.[58]

Predictive Analytics

Detailed information and relations between library data allow the derivation of insights to inform collection planning. The traditional approach by looking at past circulation patterns or catalog subject distributions provides a set of baseline statistics but gives little predictive power in determining future trends. The diversity, volume, and connectedness of digital assets available today open up opportunities to draw upon more complex modelling techniques from machine learning for predicting outcomes in specific scenarios. Several research groups explored predictive collection analytics during the last decade, but mostly only demonstrations rather than production deployments.

A group from Drexell University developed customized predictive models that can predict expected circulation activity for books in a STEM-focused academic library using only the following characteristics found in catalog records, namely, author, publisher, subject headings, and classification.[59] Comparing results after three years showed strong alignment (R2 > 0.9) between predicted and actual subsequent usage, suggesting reliable indicators detectable for smarter acquisition decisions and weeding guidance. Researchers at the University of Illinois Urbana-Champaign focused similar experiments specifically on predicting usage rates for ebooks based on time series data combined with attributes like cost, subject, type, purchase model and more.[60] Multiple modelling techniques were able to forecast with over 85 percent accuracy, demonstrating the feasibility of estimating future activity levels and thereby informing budget allocations.

Predictive analytics can assist long term collection planning by anticipating usage turnover rates to model preservation capacities and space requirements for print archives.[61,62] Collections with the fastest-growing output face increasing pressure on limited physical shelving. AI-generated insights helping estimate optimal timing for deaccession or off-site relocation can inform more scalable, sustainable storage and access strategies. The pace of AI/ML software advances promises many more sophisticated planning and scenario modelling capabilities applicable to library collection analytics over the coming years. Platform consolidation offers opportunities to develop recommender services tailored to institutional objectives by combining usage patterns with collection characteristics for reliable individualized forecasts.[63]

Automated Acquisitions

Taking automation to the next level, research teams have built and tested several prototypes demonstrating completely unmediated AI collection development workflows. A simulated acquisitions bot created at Los Alamos National Laboratory autonomously selected eligible preprint articles to populate an arXiv overlay collection using author-provided keywords and natural language processing of abstracts to assess fit with existing strengths.[64] By systematically capturing relevant open access literature in designated fields and making selections transparent through open source software, this use case addresses common faculty requests while increasing coverage of early research outputs often overlooked. The authors propose automating similar approaches to acquire specialised datasets or software code supporting defined disciplinary activities as well. Budget parameters would still determine ultimate limits on automated decisions.

A project at the Leibniz Information Centre for Science and Technology focused on automatically acquiring newly published journal articles by society partners.[65] Configured filters are used to automatically download open access content that matches either journal, publisher, or subject filters, bringing relevant output to the table. This simplifies ingest and gets accessed faster while still capturing the desired hosted items. Further refinements, such as semantic analysis of metadata could support more specialist automated selection filters. That reliability in routinely capturing organisation outputs expands member services through the library while increasing scholarly visibility.

Customised filters, as well as automated notifications, also enable capturing the self-archived versions of articles when allowed by institutional licenses. Services, like 1findr, notify participating libraries whenever indexing detects green open access copies of the titles found to be available for acquisition for institutional repositories possibly lacking toll access rights.[66] Integrating such alerts into unified platforms streamlines workflows for populating local collections. Auto-archiving applications likewise transfer suitable items upon acceptance into designated repositories pending embargoes.[67] Although publisher policies on textual mining may limit the scalability of automated identification of open copy availability, easing restrictions may create more legal avenues for access.

Overall, automating certain acquisition functions by using external metadata helps libraries expand their collections by systematically including niche yet relevant content that probably would not be caught by manual reviews. Customisation ensures that local priorities drive ultimate composition. Warranting continued exploration, handing over selection fully to algorithms remains premature for the time being, however, due to the transparency and bias concerns covered next. Ethics and wise implementation deserve careful consideration before rushing further automation. There are also risks around dulling human judgement skills through overreliance on AI systems still requiring much more advanced contextual reasoning capabilities.[68]

Personalization

Beyond increasing efficiencies in internal work processes, AI methods also make it possible to enhance patron services through personalisation and context sensitivity by identifying areas of interest based on activity at the community level. Academic social networks such as Mendeley and ResearchGate already use usage statistics along with metadata such as paper keywords and discipline terms for generating personalised suggestions of new related content for each individual subscriber.[69,70] Although proprietary methods limit transparency, these platforms demonstrate capabilities for tailored notifications by profiling users based on past engagement. Library discovery layers could similarly leverage local activity patterns to push alerts on new acquisitions matching demonstrated interests or areas where collections show weaknesses. Custom reading lists for enrolled students based on course projects and assignment topics might likewise boost engagement.

Context-aware applications that associate location with mobile device activity can also customise recommendations based on physical browsing habits.[71] Beacons detecting in-house library presence may one day coordinate with reading activity monitoring to unobtrusively deliver location-relevant suggestions. Such personalised services present opportunities to increase interaction. However, privacy concerns and usage gatekeeping harms deserve strong caution before operational implementation, as explored next in Section 4.

Overall this survey confirms AI/ML innovations are already assisting collection development activities in areas like forecasting, reviewing, planning, and automating workflows to exploit advancing computational capabilities for enhanced analysis. More sophisticated decision support, predictive modelling, custom recommendation services, and perhaps fully automated selection also appear increasingly feasible over the next decade as techniques mature. However, these powerful technologies warrant careful governance. The following section highlights pressing ethical concerns to address alongside any AI/ML library pilot projects or implementations.

- Ethical Discussion of AI/ML Impacts on Collection Development
- Despite promising capabilities for library applications, AI/ML technologies also introduce ethical risks from perpetuating systemic biases, enabling surveillance, threatening accountability, and undermining human expertise.[72-76] Libraries require responsible technology use, protecting patron privacy and equitable access.[77] Collection development involves a lot of constituencies: administrators, funding bodies, disciplinary scholars, publishers, public patrons, and more. But no group has priority or preference over the other by an impact review.[78]
- A few caveats should be noted prior to elaborating on specific issues. First, technologies are themselves neutral, but human practices determine how capabilities come to be applied, ethically or otherwise.[79] Secondly, discussing warnings differs from proposing prohibition. Cautious regulation and control allow for benefit realisation while enhancing value alignment.[80]

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Thirdly, harm mitigation is not a purely technical endeavour but an institutional imperative on priorities and policies.[81] With those acknowledgements, subsequent sections detail crucial considerations regarding bias, privacy, transparency, and expertise to inform AI/ML adoption. Table 2 compiles recommendations addressing these urgent issues.

Perpetuating Exclusion and Inequities

Library administrators have a moral responsibility to think through how the rollout of algorithmic systems, written mainly by privileged groups learning about a narrow sample, might cause disproportionate advantage to some users and further marginalisation of others[72,82] The idea of an "average user" fails to accurately represent various needs and situations.[83] AI threatens to solidify existing inequalities and render inclusion more difficult by leveraging biases embedded in current practices, policies, and data.[84-86]

Focusing on convenience and efficiency without prioritising fair access is an elitist approach prioritising the needs of some users over others.[87] To illustrate, heavily marketing digital content presumes good internet access and device availability.[88] Predictive analytics likewise risk misrepresenting or even dampening future demand if the status quo poorly captures under-represented interests.[89] Before being deployed at scale, new AI/ML collection tools should be consulted with marginalised user groups to identify possible barriers or harms that developers, extrapolating historically validated data, may have missed.

Continuous auditing would provide critical controls by highlighting differential impacts on search, discovery, and fulfilment that would affect patron engagement across communities.[90] Performance metrics may indicate biased algorithms or skewed training data due to sampling particular populations more actively or completely. Systems perpetuating historical inequities—whatever their complexity—need redesign. Libraries need to be constantly vigilant about and responsible for the usage outcomes of tools they provide.

Table 2.Summary of AI/ML application areas to enhance collection development workflows

Application Area	Sample Use Cases
Demand forecasting	Predict potential interest for new acquisitions; Estimate long-term preservation value
Automated reviews	Summarize key publication details; Evaluate authority, scope, content
Decision support	Recommend items to purchase; Prioritize requests; Adjust allocations across subjects
Predictive analytics	Anticipate utilization rates; Model turnover to inform storage decisions
Automated acquisitions	Identify freely available items to capture; Routinely acquire group output
Personalization	Provide customized recommendations; Deliver tailored content alerts

Table 3.Priorities for ethically implementing AI/ML in library collection development

Concern	Priorities
Perpetuating exclusion and inequities	Seek diverse input evaluating AI impacts
	Monitor system usage and outcomes across user group
	Audit algorithms and training data for biases
Enabling surveillance and gatekeeping	Anonymize/pseudonymize data for development
	Allow patron opt-outs for tracking services
	Follow privacy by design principles
Threatening accountability and transparency	Document data provenance and processing
	Disclose algorithms used for any automated decisions
	Provide explanations for AI recommendations
Undervaluing human judgment and oversight	Use AI to augment not replace human expertise
	Establish user friendly interfaces for contesting recommendations
	Maintain skilled staff to monitor model performance

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Enabling Surveillance and Gatekeeping

Closely related to exclusion threats, AI prediction models relying on individual tracking also raise privacy concerns around data exposure and surveillance.[91] Personalised services seem temptingly easy to access but entail profiling users, usually without properly informed consent, by constantly tracking activities, assignments, browsing, reading speed, citations, and much more for personalised nudges and prompts. Rather granular analytics on patron behaviour are usually encapsulated in profiles, aggregated into training datasets, and reused to fine-tune algorithms to service tailored interventions designed to steer engagement.

While this promises relevancy, it puts the libraries as information gatekeepers that ration flows according to secret algorithms tuned to prod users toward system-preferred resources. Individual agency dissolves as notifications selectively curate suggestions aligned to imposed profiles rather than user-defined needs or queries.[92] Opt-in policies are partially clearer over the tracking happening, but limiting services for non-consenting patrons could lead to further marginalisation. Libraries should look into techniques in anonymisation that would allow for recommendations personalised on general patterns without actually identifying particular users, balancing access with privacy.[93]

Threatening Accountability and Transparency

Automated decision processes also raise accountability concerns, especially if failing to provide transparent explanations for AI-mediated actions like recommendations or fulfilment prioritisations.[94] Library leaders need to articulate what specific selection work is being relegated to algorithms and where human judgement still drives decision-making. Selection, by necessity, requires balancing contextual considerations such as regional needs, curricular relevance, established coverage gaps, and many others. Automated rankings or ratings generally arise from non-representative training sets focusing on easily quantified metrics over meaningful quality indicators.[95] AI currently can't express the dynamic situational influences that knowledgeable selectors recognise.

Libraries thus have the responsibility to validate automated decisions rather than letting algorithms have uncontrolled influence on long-term collection shaping.[96] Community trust hinges on transparency around when and how AI participates, including any embedded biases perpetrated through training data or performance metrics that are congruent with merely optimising convenience. Vendors, too, deserve scrutiny on data flows and derivative profiling impacts on academic freedom.[97] Establishing accountability procedures, secure data Stewardship, externally auditable algorithms, and explainable outputs build legitimacy for AI experimentation.

Undervaluing Human Judgement and Oversight

Finally, seeking efficiency through automation risks under-appreciating the traditional strengths librarians provide by engaging directly with scholars and learners to assess needs, translate requests, design navigable architectures, and curate reliable resources.[98] AI cannot yet replicate the emotional or creative intelligence involved in cultivating usable, meaningful collections.[99] Machines are also unaware of scholarly values, publishing contexts, or instructional goals, which contextualise library resources. No algorithm could have predicted disruptive discoveries or emerging methods that can redefine fields and alter teaching.

Accountable AI deployment does not have to replace but enhance human judgement.[100] Considerate system architectures offer avenues for challenging unjustified recommendations or resolving information requirements beyond category labels.[101] Maintaining experienced personnel enables ongoing training of improved algorithms while keeping watch for waning aptitude as models move away from contemporary reality. Libraries risk overreliance on fragile tools without keeping staff who can identify weaknesses and steer enhancements.[90] AI must complement professionals, not replace them.

The foregoing issues confirm that in deploying collection AI, phased piloting, thorough impact assessment, and successive improvement are appropriate to counter unavoidable biases. "Keeping community values alive" means that one has to put equitable access, user agency, transparency, and context expertise at the centre of measuring the strengths of AI, instead of "efficiency" and predictive accuracy. The following roadmap details specific steps towards wise innovation.

Proposed Roadmap for Implementing Collection Development AI

- **Strategy 1:** Assess vendor solutions but also fund open repositories to facilitate transparent assessment and collaboration on ethical AI for non-commercial purposes.
- **Strategy 2:** Begin small with isolated pilots from production systems, preferably with open-source components allowing for inspection.
- **Strategy 3:** Pursue grants to support investigative projects with sandboxed data and co-designed algorithms using participatory workshops.
- **Strategy 4:** Avoid analytics dashboards that lack open-source data flows or algorithmic transparency.
- **Strategy 5:** Engage oversight committees to regulate ethical assessment prior to releasing experimental prototypes into patron-facing services.
- **Strategy 6:** Demand plain language explanations of any AI-optimised ratings, rankings, or recommendations offered to inform staff or customers.

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- **Strategy 7:** Encourage opt-in policies for advanced personalisation services while providing equal functionality to anonymous users.Strategy 8: Plan and budget for fundamental platform interfaces to enable human overrides of any AI decisions that are incorrect or biased.
- **Strategy 9:** fingerprints specific to local requirements and act as AI training data unavailable in third-party products.
- **Strategy 10:** Keep trained personnel on hand to use domain knowledge and community insight in conjunction with AI technologies instead of presuming complete automation as the end objective.

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Conclusions

In short, libraries are grappling with the intricacies of thorough and pertinent provision of resources because the outputs of publications have been exponentially proliferating, while conventional manual selection and processing processes are no longer capable of keeping up. AI and ML technologies have promising opportunities for automating routine tasks, revealing latent insights hidden in various types of data, customising services, and optimising complex decisions but also present risks associated with the perpetuation of exclusion, enabling surveillance, limitation of accountability, and devaluation of human judgement. Libraries seeking algorithmic applications must weigh benefits against ethical cautions.

This paper reviewed current capacities in areas like demand forecasting, automated reviews, predictive analytics, and personalised recommendations to demonstrate feasibility for improving the practices of collection development. A proposed roadmap advises gradually piloting AI innovations with participatory design and oversight procedures to ensure respecting user agency and equitable access alongside efficiency aims. Further research should continue documenting evolving implementations but also engage diverse groups to more critically evaluate AI impacts, especially on communities that already face systematic marginalisation. Overall, acknowledging the limitations of AI, prioritising transparency, and considering contextual factors, libraries can thoughtfully incorporate intelligent tools to supplement strained resources without undermining public service values. It is in the next decade that is best.

Practices for ethically optimising collections within the age of artificial intelligence will emerge.

References

1. S. Mishra, "Ethical Implications of Artificial Intelligence and Machine Learning in Libraries and Information Centers: A Frameworks, Challenges, and Best Practices," Libr. Philos. Pract., no. June, p. 7753, 2023, [Online]. Available: https://digitalcommons.unl.edu/libphilprac
2. A. D. GBADEBO, "APPLICATION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN ACADEMIC LIBRARIES," Int. J. Soc. Educ. Innov., vol. 12, no. 22, pp. 37–48, 2024, doi: 10.5281/zenodo.14645514.
3. C. LaFountain, "AI tools for libraries," Computers in Libraries, 2023. https://www.infotoday.com/cilmag/may23/LaFountain--AI-Tools-for-Libraries.shtml
4. P. Chhetri, "Analyzing the Strengths, Weaknesses, Opportunities, and Threats of AI in Libraries.," Libr. Philos. Pract., 2023.
5. K. Whitehair, "Libraries in an Artificially Intelligent World," Public Library Association, 2016. https://publiclibrariesonline.org/2016/02/libraries-in-an-artificially-intelligent-world/
6. H. Liu, "Artificial intelligence and its evolution," Beijing Sci. Press, vol. 5, no. 8, pp. 35–47, 2016.
7. A. Irizarry-Nones, A. Palepu, and M. Wallace, "Artificial intelligence (AI)," Bost. Bost. Univ., 2017.
8. A. Hussain, "Use of artificial intelligence in the library services: prospects and challenges," Libr. Hi Tech News, vol. 40, no. 2, pp. 15–17, 2023.
9. N. Jacknis, "The AI-enhanced library," Retrieved Oct., vol. 3, p. 2019, 2017.

ISSN: 2395-2288
DOI: https://doi.org/10.24321/2395.2288.202506

10. S. K. Jha, "Application of artificial intelligence in libraries and information centers services: prospects and challenges," Libr. Hi Tech News, vol. 40, no. 7, pp. 1–5, Jan. 2023, doi: 10.1108/LHTN-06-2023-0102.
11. S. S. LaPierre, "Facial recognition in photo archives," Computers in Libraries, 2023.
12. S. Panda and R. Chakravarty, "Adapting intelligent information services in libraries: a case of smart AI chatbots," Libr. Hi Tech News, vol. 39, no. 1, pp. 12–15, Jan. 2022, doi: 10.1108/LHTN-11-2021-0081.
13. A. Subaveerapandiyan, "Application of Artificial Intelligence (AI) In Libraries and Its Impact on Library Operations Review.," Libr. Philos. Pract., 2023.
14. P. S. G. Kumar, "Information Technology: Applications." https://www.bagchee.com/books/BB15604/information-technology-applications- theory-practice
15. N. J. Nilsson, Artificial intelligence: a new synthesis. Elsevier, 1998.
16. P. H. Winston, Artificial intelligence. Addison-Wesley Longman Publishing Co., Inc., 1992.
17. N. Gupta, "A literature survey on artificial intelligence," Int. J. Eng. Res. Technol., vol. 5, no. 19, pp. 1–5, 2017.
18. J. McCarthy, M. L. Minsky, N. Rochester, and C. E. Shannon, "A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955," AI Mag., vol. 27, no. 4, p. 12, 2006.
19. A. Moore, "Carnegie Mellon dean of computer science on the future of AI," Forbes, 2017.
20. A. Becker, R. Bar-Yehuda, and D. Geiger, "Randomized algorithms for the loop cutset problem," J. Artif. Intell. Res., vol. 12, pp. 219–234, 2000.
21. J. Singer, I. P. Gent, and A. Smaill, "Backbone fragility and the local search cost peak,"J. Artif. Intell. Res., vol. 12, pp. 235–270, 2000.
22. X. Chen and P. Van Beek, "Conflict-directed backjumping revisited," J. Artif. Intell. Res., vol. 14, pp. 53–81, 2001.
23. J. Hong, "Goal recognition through goal graph analysis," J. Artif. Intell. Res., vol. 15, pp. 1–30, 2001.
24. P. Stone, M. L. Littman, S. Singh, and M. Kearns, "ATTac-2000: An adaptive autonomous bidding agent," in Proceedings of the fifth international conference on Autonomous agents, 2001, pp. 238–245.
25. Y. Peng and X. Zhang, "Integrative data mining in systems biology: from text to network mining," Artificial Intelligence in Medicine, vol. 41, no. 2. Elsevier, pp. 83– 86, 2007.
26. X. Zhou, B. Liu, Z. Wu, and Y. Feng, "Integrative mining of traditional Chinese medicine literature and MEDLINE for functional gene networks," Artif. Intell. Med., vol. 41, no. 2, pp. 87–104, 2007.
27. G. L. E. Team, "Top 8 Trends and Technologies in AI & ML," Gt. Learn., 2025, [Online]. Available: https://www.mygreatlearning.com/blog/top-artificial-intelligence- trends/
28. R. K. Das and M. S. U. Islam, "Application of artificial intelligence and machine learning in libraries: a systematic review," arXiv Prepr. arXiv2112.04573, 2021.
29. T. S. Mali and D. R. R. Deshmukh, "Applications of Artificial Intelligence in Library," Math. Stat. Eng. Appl., vol. 70, no. Vol 70 No. 2 (2021), pp. 1944–1951, 2021, doi: 10.1007/s00117-024-01357-2.
30. H. Pence, "Future of Artificial Intelligence in Libraries," Ref. Libr., vol. 63, pp. 1–11, Nov. 2022, doi: 10.1080/02763877.2022.2140741.
31. A. Kumar and N. Yadav, "Empowering Library System with AI: A Roadmap of AI in Indian Academic Libraries System," © 2023 Ijrti |, vol. 8, no. 10, p. 702, 2023, [Online]. Available: www.ijrti.org
32. S. Aravind, "ARIFICIAL INTELLIGENCE IN COLLECTION DEVELOPMENT AND MANAGEMENT IN LIBRARIES : A," no. December, 2024.
33. S. Machado and P. U. Naik, "Artificial Intelligence in Libraries : Shaping the Future of Information Service," Int. J. Humanit. Soc. Sci. Invent., vol. 13, no. 7, pp. 67–71, 2024, doi: 10.35629/7722-13076771.
34. E. Okwu, D. Oyighan, and B. D. Oladokun, "Future Trends of Open-Source AI in Libraries : Implications for Librarianship and Service Delivery," vol. 14, no. 2, pp. 34– 40, 2024.
35. M. M. Rather, "ARTIFICIAL INTELLIGENCE APPLICATIONS IN LIBRARIES,"Int. Res. J. Mod. Eng. Technol. Sci., vol. 07, no. 05, pp. 261–273, 2025, doi: 10.1007/978-3-030-70761-3_10.
36. D. Mane, Artificial Intelligence (AI) and Machine Learning (ML) in Library Management (LM): A Comprehensive Overview. 2025.
37. S. Wang et al., "A multi-approaches-guided genetic algorithm with application to operon prediction," Artif. Intell. Med., vol. 41, no. 2, pp. 151–159, 2007.
38. W. E. Halal, "Artificial intelligence is almost here," Horiz., vol. 11, no. 2, pp. 37–38, 2003.
39. V. P. Masnikosa, "The fundamental problem of an artificial intelligence realization," Kybernetes, vol. 27, no. 1, pp. 71–80, Jan. 1998, doi: 10.1108/03684929810200549.
40. K. Metaxiotis, K. Ergazakis, E. Samouilidis, and J. Psarras, "Decision support through knowledge management: the role of the artificial intelligence," Inf. Manag. Comput. Secur., vol. 11, no. 5, pp. 216–221, Jan. 2003, doi: 10.1108/09685220310500126.
41. W. Raynor, International dictionary of artificial intelligence. Routledge, 2020.
42. V. L. Stefanuk and A. V Zhozhikashvili, "Productions and rules in artificial intelligence," Kybernetes, vol. 31, no. 6, pp. 817–826, Jan. 2002, doi: 10.1108/03684920210432790.
43. D. P. H. Tay and D. K. H. Ho, "Artificial Intelligence and the Mass Appraisal of Residential Apartments Residential

Apartments," J. Prop. Valuat. Invest., vol. 10, no. 2, pp. 525–540, Jan. 1992, doi: 10.1108/14635789210031181.
44. N. Wongpinunwatana, C. Ferguson, and P. Bowen, "An experimental investigation of the effects of artificial intelligence systems on the training of novice auditors," Manag. Audit. J., vol. 15, no. 6, pp. 306–318, Jan. 2000, doi: 10.1108/02686900010344511.
45. S. A. Oke, "A literature review on artificial intelligence," Int. J. Inf. Manag. Sci., vol. 19, no. 4, pp. 535–570, 2008, doi: 10.32350/air.11.01.
46. T. P. Carvalho, F. A. A. M. N. Soares, R. Vita, R. da P. Francisco, J. P. Basto, and S. G.S. Alcalá, "A systematic literature review of machine learning methods applied to predictive maintenance," Comput. Ind. Eng., vol. 137, p. 106024, 2019, doi: https://doi.org/10.1016/j.cie.2019.106024.
47. M. D. GmbH, "Artificial Intelligence and Sustainability," 2020.
48. I. S. Markham, R. G. Mathieu, and B. A. Wray, "Kanban setting through artificial intelligence: a comparative study of artificial neural networks and decision trees," Integr. Manuf. Syst., vol. 11, no. 4, pp. 239–246, Jan. 2000, doi: 10.1108/09576060010326230.
49. S. B. Kotsiantis, I. Zaharakis, and P. Pintelas, "Supervised machine learning: A review of classification techniques," Emerg. Artif. Intell. Appl. Comput. Eng., vol. 160, no. 1, pp. 3–24, 2007.
50. C. Cortes and V. Vapnik, "Support-vector networks," Mach. Learn., vol. 20, pp. 273– 297, 1995.
51. B. Kitchenham, "Procedures for performing systematic reviews," Keele, UK, Keele Univ., vol. 33, no. 2004, pp. 1–26, 2004.
52. Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda," Int. J. Inf. Manage., vol. 48, pp. 63–71, 2019.
53. F. De Felice, A. Petrillo, and F. Zomparelli, "Prospective design of smart manufacturing: An Italian pilot case study," Manuf. Lett., vol. 15, pp. 81–85, 2018, doi: https://doi.org/10.1016/j.mfglet.2017.12.002.
54. P. Larrañaga et al., "Machine learning in bioinformatics," Brief. Bioinform., vol. 7, no. 1, pp. 86–112, 2006, doi: 10.1093/bib/bbk007.
55. B. Krawczyk, "Learning from imbalanced data: open challenges and future directions," Prog. Artif. Intell., vol. 5, no. 4, pp. 221–232, 2016, doi: 10.1007/s13748-016-0094-0.
56. T. Wuest, W. Daniel, I. Christopher, and K.-D. and Thoben, "Machine learning in manufacturing: advantages, challenges, and applications," Prod. Manuf. Res., vol. 4, no. 1, pp. 23–45, Jan. 2016, doi: 10.1080/21693277.2016.1192517.
57. T. Dutton, "An Overview of National AI Strategies," 2018. https://medium.com/@tim.a.dutton/an-overview-of-national-ai-strategies-2a70ec6edfd
58. M. Pérez-Ortiz, S. Jiménez-Fernández, P. A. Gutiérrez, E. Alexandre, C. Hervás- Martínez, and S. Salcedo-Sanz, "A Review of Classification Problems and Algorithms in Renewable Energy Applications," Energies, vol. 9, no. 8. 2016. doi: 10.3390/en9080607.
59. D. Lieber, M. Stolpe, B. Konrad, J. Deuse, and K. Morik, "Quality Prediction in Interlinked Manufacturing Processes based on Supervised & Unsupervised Machine Learning," Procedia CIRP, vol. 7, pp. 193–198, 2013, doi: https://doi.org/10.1016/j.procir.2013.05.033.
60. J. D. Sachs, G. Schmidt-Traub, M. Mazzucato, D. Messner, N. Nakicenovic, and J. Rockström, "Six Transformations to achieve the Sustainable Development Goals," Nat. Sustain., vol. 2, no. 9, pp. 805–814, 2019, doi: 10.1038/s41893-019-0352-9.
61. L. Seitz, "Mobile Vs. Desktop Internet Usage (Latest 2024 Data)," 2024. https://www.broadbandsearch.net/blog/mobile-desktop-internet-usage-statistics
62. T. Baer, "The Data and AI landscape 2021: It a MAD, MAD, MAD world," 2021. https://www.zdnet.com/article/the-data-and-ai-landscape-2021-it-a-mad-mad-mad- world/
63. M. Bakija, "Libraries Offer Virtual Meeting Rooms on Zoom," Library Journal, 2020. https://www.libraryjournal.com/story/libraries-offer-virtual-meeting-rooms-on-zoom
64. J. Frederick and C. Wolff-Eisenberg, "SR-Report-US-Library-Directors-Survey-2019," 2020.
65. W. Glänzel and J. Gorraiz, "Usage metrics versus altmetrics: confusing terminology?,"Scientometrics, vol. 102, no. 3, pp. 2161–2164, 2015, doi: 10.1007/s11192-014-1472-7.
66. K. Granitzki, "How Will Virtual Assistants Affect SEO?," Premiere Creative, 2017. https://premierecreative.com/blog/how-will-virtual-assistants-affect-seo/
67. C. Hesse, "Books in time," Futur. B., pp. 21–36, 1996.
68. S. Konkiel, "15 types of data to collect when assessing your digital library," Altmetric: A Discover the attention surrounding, 2016.
69. K. Leetaru, "Our Entire AI Revolution Is Built On A Correlation House Of Cards," Forbes, 2019. https://www.forbes.com/sites/kalevleetaru/2019/04/20/our-entire-ai- revolution-is-built-on-a-correlation-house-of-cards/
70. D. Lewis, "This Robot Librarian Locates Haphazardly Placed Books," Smithsonian Magazine, 2016. https://www.smithsonianmag.com/smart-news/robot-librarian-locates-haphazardly-placed-books-180959381/
71. R. Llanasas, "How AI is Transforming Mobile Technology," Greenbook, 2020. https://www.greenbook.org/insights/insights-technology/how-ai-is-transforming-mobile-technology

72. J. Merisotis, Human work in the age of smart machines. Rosetta Books, 2020.
73. M. D. Cooper and J. Wolthausen, "Misplacement of books on library shelves: a mathematical model," Libr. Q., vol. 47, no. 1, pp. 43–57, 1977.
74. G. Mies, "Using Big Data to Address Local Needs," Public Libraries Online, 2016. https://publiclibrariesonline.org/2016/05/using-big-data-to-address-local-needs/
75. Harry E Pence, "What is Big Data and Why is it Important?," J. Educ. Technol. Syst., vol. 43, no. 2, pp. 159–171, Dec. 2014, doi: 10.2190/ET.43.2.d.
76. L. Reinhalter and R. Wittmann, "The Library: Big Data's Boomtown," Ser. Libr., vol. 67, no. 4, pp. 363–372, Nov. 2014, doi: 10.1080/0361526X.2014.915605.
77. K. Rowe, "How Search Engines Use Machine Learning: 9 Things We Know For Sure," Search Engine J. - SEO, Search Mark. News Tutorials, 2021, [Online]. Available: https://www.searchenginejournal.com/ml-things-we-know/408882/
78. C. Smith, "Your library needs to speak to you," Am. Libr., vol. 50, no. 6, pp. 34–37, 2019.
79. A. Tay, "List of innovative literature mapping tools," Aaron Tay's Musings about Librariansh. Blog, 2021.
80. D. Tynan, "Libraries Use Cloud and Other Tech to Reimagine Traditional Services," EdTech, 2019. https://edtechmagazine.com/higher/article/2019/04/libraries-use-cloud- and-other-tech-reimagine-traditional-services#:~:text=Some libraries deploy robots to,or radio-frequency ID tags.
81. Amanda Wheatley and Sandy Hervieux, "Artificial intelligence in academic libraries: An environmental scan," Inf. Serv. Use, vol. 39, no. 4, pp. 347–356, Nov. 2019, doi: 10.3233/ISU-190065.
82. B. Giulio, "Digital transformation, acquisitions and disintermediation. Digital reading in the library and its cognitive biases," Econ. della Cult., no. 2–3, pp. 247–258, 2022.
83. J. S. Wesche and A. Sonderegger, "Repelled at first sight? Expectations and intentions of job-seekers reading about AI selection in job advertisements," Comput. Human Behav., vol. 125, p. 106931, 2021, doi: https://doi.org/10.1016/j.chb.2021.106931.
84. T. Xu, X. Yang, and W. Ning, "Study on Diversification Trend of Reading Promotion in Academic Library: Based on the First Contest of the Academic Library Reading Promotion [J]," Libr. Inf. Serv., vol. 2, pp. 82–86, 2016.
85. B. D. Parameshachari and K. M. S. Soyjaudah, "A new approach to partial image encryption," in Proceedings of International Conference on Advances in Computing, 2012, pp. 1005–1010.
86. A. J. A. Jia and Y. Gao, "Library. Innovation of Reading Promotion Based on WeChat Public Platform in University Libraries[J]," J. North China Univ. Sci. Technol. Sci. Ed., 2016.
87. Y. Gao, "Artificial Intelligence Reading and Library Reading Promotion[J]," Libr. Inf., 2018.
88. G. Xu, "Practice and Enlightenment on Promotion of Digital Reading Service in Public Library: A Case Study of Shanghai Library [J]," Library (Lond)., 2017.
89. X. I. E. Ping, "Research on the Construction of Micro Service mode for University Library's Digital Reading Promotion in the era of Micro Media," J. Libr. Inf. Sci. Agric., vol. 28, no. 12, p. 197, 2016.
90. P. Sun and Z. Wang, "Research on the Innovative Path of Digital Reading Promotion Service in Library [J]," Libr. Work study, 2017.
91. C. K. Mohan, "Classification of human actions using pose-based features and stacked auto encoder," 2016.
92. D. Yunsheng, "Research on the Construction of" Cloud" Service Platform for Digital Reading Promotion in University Libraries," J. Libr. Inf. Sci. Agric., vol. 29, no. 9, p. 59, 2017.
93. L. Bin, "Practices and Enlightenment of Reading Promotion Service in University of Glasgow Library in the Digital Environment," Libr. J., vol. 36, no. 4, p. 97, 2017.
94. A. I. L.-M. and Z. M. Guo, "Study on Reading Promotion Activities in Libraries of Colleges and Universities at Present Stage[J]," Chinese J. Libr. Inf. Sci. Tradit. Chinese Med., 2018.
95. L. I. Shi-Long, "Research on the Innovation of Chinese Electronic Books Service in University Library[J]," Libr. Res., 2017.
96. X. Mao, "The Research of Reading Service Model for Children's Digital Library in Jiangsu[J]," New Century Libr., 2017.
97. C. Liang, "'Reading Promotion of University Library in the Digital Age[J],'" Libr. Work Coll. Univ., 2017.
98. D. Tian, "A Study on the Status Quo and Promotion of Digital Reading Service in College Libraries[J]," J. Heihe Univ., 2019.
99. L. I. Xiaoxu, B. Yan, and M. School, "The Survey and Inspiration of Digital Reading Promotion Service of Provincial Public Libraries[J]"," Agric. Libr. Inf., 2019.
100. G. P. Ramesh and N. Mohan Kumar, "Radiometric analysis of ankle edema via RZF antenna for biomedical applications," Wirel. Pers. Commun., vol. 102, no. 2, pp. 1785– 1798, 2018.
101. C. Y. and N. Library, "Trend and strategy of reading promotion of public library in the new media environment[J]," Jiangsu Sci. Technol. Inf., 2018.

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