ISSN: 2393-8048
International Advance Journal of Engineering, Science and Management (IAJESM)
Multidisciplinary, Multilingual, Indexed, Double Blind, Open Access, Peer-Reviewed, Refereed-International Journal.
SJIF Impact Factor = 8.35, January-June 2026, Published on 28th February 2026

Smart Libraries in Smart Education: Integrating AI Technologies for Personalized Learning Support

Suneel Kumar Bhat, Sr. Librarian, MIER College of Education, B.C. Road, Jammu, India
Email: suneel.bhat@miercollege.in

Abstract

The convergence of artificial intelligence (AI) and library science has catalyzed the emergence of a new paradigm: the smart library—a dynamic, data-driven ecosystem capable of adapting to learners' individual needs in real time. This article examines how AI technologies, including machine learning, natural language processing (NLP), intelligent recommendation systems, chatbot-assisted reference services, and adaptive learning platforms, are being integrated into academic and public library infrastructures to support personalized learning. Drawing on peer-reviewed literature, institutional case studies, and emerging theoretical frameworks, the paper argues that smart libraries represent a fundamental transformation in how knowledge is curated, accessed, and pedagogically leveraged within smart education environments. The study explores the technical architecture of AI-enabled library systems, their pedagogical implications, ethical considerations surrounding data privacy and algorithmic bias, and the challenges of implementation across diverse institutional contexts. Findings suggest that while AI-enhanced libraries significantly improve learning outcomes, engagement, and resource discovery efficiency, their success depends on equitable design principles, robust digital infrastructure, and ongoing collaboration between library professionals, educators, and technology developers. The article contributes an integrated conceptual model—the Smart Library Learning Ecosystem (SLLE)—as a framework for understanding and guiding the development of next-generation library services in the context of smart education.

Keywords: Artificial intelligence in libraries, smart education, personalized learning, natural language processing, adaptive learning systems, intelligent recommendation systems, library automation, digital transformation.

Introduction

The twenty-first century has ushered in a profound reconfiguration of educational landscapes, driven by the proliferation of digital technologies and an increasing demand for learner-centred pedagogical approaches. Within this transformation, libraries—long regarded as static repositories of physical knowledge—are undergoing a radical metamorphosis. The concept of the "smart library" has emerged as a response to the dual imperatives of technological modernization and the escalating complexity of learner needs. Smart libraries are not merely digitized collections; they are intelligent, responsive environments that leverage data science and artificial intelligence to anticipate, adapt to, and enhance the learning experiences of their users (Breeding, 2021).

Simultaneously, the broader educational ecosystem has been redefined by the concept of "smart education," a framework that envisions learning as a seamless, personalized, and technology-mediated process. Smart education integrates cloud computing, the Internet of Things (IoT), big data analytics, and AI to create what Zhu et al. (2016) describe as a SMART environment—one that is Self-directed, Motivated, Adaptive, Resource-enriched, and Technology-embedded. Within this framework, the library is not a peripheral component but a central node in the knowledge architecture of smart educational institutions.

Despite the growing literature on both smart libraries and smart education as distinct domains, relatively little scholarly attention has been devoted to examining the integration of these two paradigms—specifically, how AI technologies embedded in library systems can actively support personalized learning. This gap is significant, given that libraries traditionally serve as the primary information infrastructure of educational institutions. Understanding how they can be re-engineered using AI to function as intelligent learning support systems has profound implications for educators, library professionals, technology developers, and policymakers.

This article addresses this gap by undertaking a comprehensive, theoretically grounded examination of the role of AI in transforming libraries into smart, personalized learning support environments. It draws on a systematic review of peer-reviewed literature published between 2016 and 2024, supplemented by institutional case studies and technical documentation from pioneering smart library initiatives. The article is organized as follows: Section 2 reviews the conceptual foundations of smart libraries and smart education; Section 3 examines specific AI technologies deployed in smart library contexts; Section 4 presents a synthesized conceptual framework—the Smart Library Learning Ecosystem (SLLE); Section 5 discusses implementation challenges and ethical considerations; Section 6 outlines future directions; and Section 7 concludes with theoretical and practical implications.

2. Conceptual Foundations: Smart Libraries and Smart Education

2.1 Defining Smart Libraries

The concept of the smart library defies a singular, universally accepted definition. However, across the scholarly literature, a cluster of defining characteristics recurs: integration of sensor-based technologies for environmental control and space management; deployment of AI-driven discovery and recommendation systems; provision of real-time, personalized user services; and the capacity for continuous learning and self-optimization based on user interaction data (Lund & Treasure-Jones, 2020). Alonso-Arévalo and Vázquez-Vázquez (2021) further characterize smart libraries as spaces in which the physical and digital are seamlessly fused—where intelligent bookshelves communicate with inventory management systems, reading spaces respond to occupancy and environmental preferences, and reference desks are augmented by virtual assistants capable of handling complex informational queries.

From a systems perspective, smart libraries rest on three interconnected pillars: smart infrastructure (IoT-enabled physical spaces), smart collections (AI-curated and dynamically updated digital and physical holdings), and smart services (personalized, context-aware user interactions mediated by AI). This tripartite architecture distinguishes the smart library from earlier models of library automation, which primarily mechanized routine workflows without achieving the kind of adaptive, user-responsive intelligence that characterizes truly smart systems (Shuhuai et al., 2010).

2.2 Smart Education as a Pedagogical Framework

Smart education, as articulated by Zhu et al. (2016), represents a departure from the conventional instruction-centred educational model toward a paradigm in which learning is continuous, context-sensitive, and dynamically tailored to individual learners. This vision is grounded in the premise that technological systems can gather, analyze, and act on granular data about learner behavior, preferences, performance, and goals to create learning pathways that are simultaneously more efficient and more deeply engaging.

The architecture of smart education systems typically comprises four layers: a data layer (comprising learner profiles, behavioral logs, and assessment data); an analytics layer (employing machine learning and statistical modelling to derive actionable insights); an application layer (including adaptive learning platforms, intelligent tutoring systems, and personalized content delivery systems); and a presentation layer (through which learners interact with the system via dashboards, mobile applications, or conversational interfaces). Libraries, positioned as the informational heart of educational institutions, have the potential to integrate meaningfully with each of these layers (Kim & Shim, 2022).

2.3 The Nexus of Smart Libraries and Smart Education

The intersection of smart libraries and smart education is theoretically rich but empirically underdeveloped. At its core, this nexus rests on a shared commitment to personalization—the principle that effective learning support must be tailored to the individual rather than delivered as a uniform service to an undifferentiated mass of users. When AI-enabled library systems are coupled with smart educational platforms, the result is an information environment that can not only surface relevant resources in response to a learner's current needs but can also anticipate future informational requirements, track knowledge acquisition over time, and adjust the nature and modality of its recommendations accordingly (Ruan et al., 2020).

This convergence also addresses a long-standing disconnect in educational technology: the gap between formal learning management systems (LMS), which manage curriculum and assessment, and library systems, which manage knowledge access. AI provides the connective tissue that can bridge these historically siloed domains, creating a unified, intelligent learning support infrastructure in which curricular content and supplementary library resources are dynamically integrated around the learner's individual trajectory (Budd, 2021).

3. AI Technologies in Smart Libraries: Applications and Implementations

3.1 Machine Learning for Personalized Recommendation

Among the most consequential applications of AI in smart libraries is the deployment of machine learning (ML) algorithms for personalized resource recommendation. Traditional library discovery systems have relied on keyword-based search and subject classification schemes—tools that, while effective for expert searchers, frequently fail to meet the needs of learners who cannot articulate their informational requirements with precision. ML-based recommendation systems address this limitation by learning from user behavior—including borrowing histories, search patterns, time-on-page metrics, and annotation activities—to build rich, multidimensional user profiles from which highly relevant recommendations can be generated (Kostagiolas et al., 2020).

Collaborative filtering, one of the foundational techniques in ML-based recommendation, identifies patterns of similarity across large populations of users to surface resources that a given learner is likely to find valuable, even if they have not explicitly searched for them. Content-based filtering, by contrast, analyzes the semantic and topical properties of resources to recommend items that are substantively similar to those a user has previously engaged with. Hybrid approaches, which combine both techniques, have been shown to outperform either method alone, particularly in academic library contexts where user populations are heterogeneous and resource collections are large and taxonomically complex (Zhang et al., 2019).

Empirical evidence for the effectiveness of ML-based recommendation in library settings is accumulating. A study by Shen et al. (2020) at a major Chinese research university found that the implementation of a deep learning recommendation model increased resource discovery rates by 34% and reduced the time learners spent searching for relevant materials by an average of 22 minutes per research session. These gains were particularly pronounced among undergraduate students and early-career researchers—populations with less developed information literacy skills—suggesting that AI recommendation has significant equity implications, effectively extending the informational advantage historically enjoyed by expert searchers to a broader population of learners.

3.2 Natural Language Processing and Conversational AI

Natural language processing (NLP) has opened new frontiers in library service delivery by enabling human-like, conversational interactions between users and library systems. Library chatbots and virtual reference assistants, powered by large language models and transformer-based architectures, can interpret queries expressed in everyday natural language, engage in multi-turn dialogues to clarify user needs, and provide substantive, contextually appropriate responses—capabilities that were beyond the reach of earlier rule-based systems (Roitman et al., 2020).

The application of NLP in libraries extends beyond chatbot interactions. Automated metadata enrichment systems use NLP to analyze the full text of documents and generate detailed, nuanced subject descriptors that far exceed the depth of human-assigned cataloguing, thereby improving the discoverability of resources within large digital collections. Sentiment analysis tools applied to user reviews and reading lists can inform collection development decisions by identifying patterns of engagement and satisfaction across different subject areas and resource types. Text summarization algorithms can produce concise, informative abstracts of lengthy documents, helping learners rapidly assess the relevance of resources before committing to in-depth reading (Chua & Leong, 2020).

Particularly significant is the emergence of NLP-powered citation assistance and research writing support tools embedded within library platforms. These tools analyze a learner's in-progress research document, identify gaps in the cited literature, and proactively recommend additional sources—a function that effectively transforms the library from a passive repository into an active collaborator in the research process. Chowdhary (2020) notes that such tools represent a qualitative shift in the library's pedagogical role, from information gateway to intellectual partner.

3.3 Intelligent Tutoring Systems and Adaptive Learning Platforms

While intelligent tutoring systems (ITS) have traditionally been associated with classroom instruction and online learning management systems, their integration with library platforms represents an important frontier in smart education. ITS embedded within library environments can monitor a learner's progress through a reading program or research project, identify conceptual gaps, and dynamically adjust the difficulty and depth of recommended resources to scaffold learning appropriately. This functionality draws on decades of research in cognitive science and educational psychology, incorporating models of knowledge states, learning trajectories, and metacognitive strategies (VanLehn, 2011).

Adaptive reading platforms—an increasingly common feature of academic library subscriptions—exemplify this integration. Platforms such as those employing spaced repetition algorithms track a learner's retention of key concepts across multiple reading sessions and strategically resurface relevant materials at the optimal point in the forgetting curve to consolidate long-term memory. When integrated with library collections, such systems can construct individualized "knowledge maps" for each learner, visualizing the relationships among concepts encountered across multiple texts and identifying areas requiring further exploration (Essa, 2016).

The pedagogical implications of ITS-library integration are significant. By coupling adaptive learning logic with the breadth of a library's collection, educational institutions can provide learners with a continuously evolving, personalized curriculum that responds not only to curricular mandates but also to the individual's own developing interests and knowledge base. This dynamic is particularly valuable in postgraduate and continuing education contexts, where learners are expected to take significant responsibility for the direction of their own intellectual development (Brusilovsky&Millán, 2007).

3.4 IoT, Sensor Technologies, and Smart Space Management

Beyond the digital services delivered through library platforms, AI and IoT technologies are reshaping the physical library environment in ways that support personalized learning. Smart library spaces are increasingly equipped with networks of sensors that monitor occupancy patterns, environmental conditions (temperature, noise levels, lighting), and the real-time location of both users and resources. This data, processed through AI algorithms, enables libraries to dynamically allocate spaces, adjust environmental parameters to support different modes of study, and provide users with real-time information about the availability of study spaces, equipment, and human expertise (Varshney et al., 2019).

RFID (Radio Frequency Identification) technology, long used in libraries for inventory management, is being augmented with AI capabilities to support more sophisticated services. Intelligent shelf-management systems use RFID data in conjunction with borrowing pattern analytics to predict demand for specific resources, proactively relocating high-demand items to more accessible locations. When integrated with a learner's personal library profile, such

ISSN: 2393-8048
International Advance Journal of Engineering, Science and Management (IAJESM)
Multidisciplinary, Multilingual, Indexed, Double Blind, Open Access, Peer-Reviewed, Refereed-International Journal.
SJIF Impact Factor = 8.35, January-June 2026, Published on 28th February 2026

systems can even prepare individualized reading kits—physical collections of resources relevant to a user's current project—for collection upon arrival at the library, streamlining the research process and reducing the cognitive load associated with resource discovery (Lee et al., 2021).

4. The Smart Library Learning Ecosystem (SLLE): A Conceptual Framework

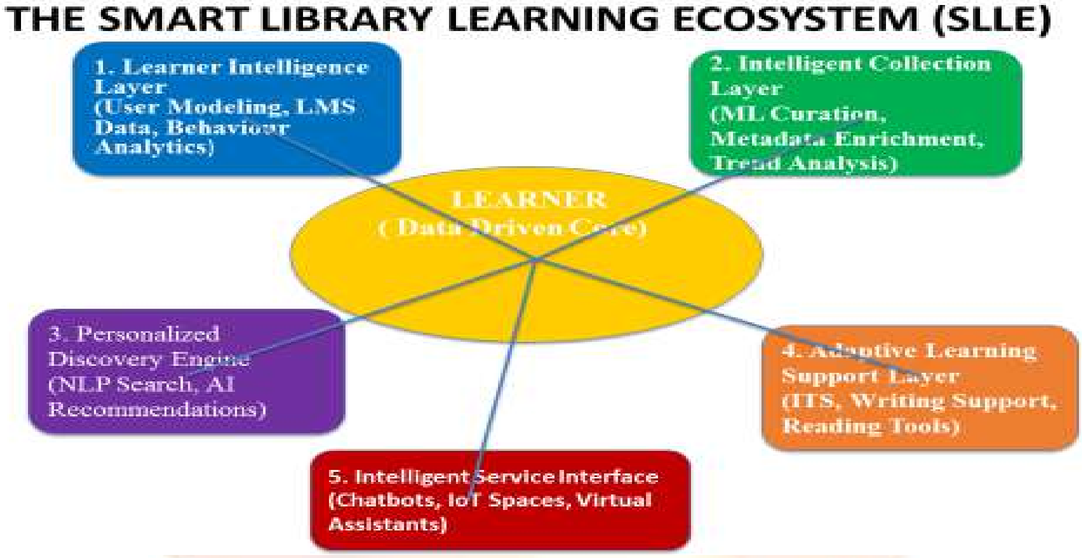

Figure 1: Smart Library Learning Ecosystem (SLLE)

The Smart Library Learning Ecosystem (SLLE) conceptualizes the AI-enabled academic library as a dynamic, learner-centric ecosystem comprising five interconnected components: (1) Learner Intelligence Layer, (2) Intelligent Collection Layer, (3) Personalized Discovery Engine, (4) Adaptive Learning Support Layer, and (5) Intelligent Service Interface. At the core of the model is the learner, whose continuous data-generating interactions inform and refine system intelligence. Through real-time analytics, machine learning, and NLP-driven personalization, the ecosystem supports adaptive resource curation, contextual discovery, and pedagogical scaffolding, thereby transforming the library from a static service provider into an intelligent, co-evolving partner in smart education environments.

Drawing on the theoretical literature reviewed above and the empirical evidence of AI applications in smart library contexts, this article proposes the Smart Library Learning Ecosystem (SLLE) as a conceptual framework for understanding and guiding the development of AI-enabled library services in smart education environments. The SLLE model conceptualizes the AI-enhanced library not as a static institution but as a dynamic, adaptive ecosystem comprising five interconnected components, operating in continuous, data-mediated interaction with the learner.

The first component, the Learner Intelligence Layer, is the ecosystem's most fundamental element. It comprises the systems and processes through which the library builds, maintains, and continuously updates a rich, multidimensional model of each learner's knowledge state, interests, goals, information literacy skills, and learning preferences. This model is constructed from diverse data streams: explicit user inputs (reading lists, research topics, stated preferences), implicit behavioral signals (search queries, browsing patterns, time spent with resources), and external data imported from connected educational systems such as the institutional LMS and student information system (Kim & Shim, 2022).

The second component, the Intelligent Collection Layer, encompasses the AI systems that manage, enrich, and curate the library's holdings. Machine learning algorithms continuously analyze usage patterns, citation networks, curricular requirements, and emerging research trends to inform collection development decisions, identify gaps in coverage, and optimize the discoverability of resources through AI-generated metadata enrichment. This layer ensures that the library's collection is not a static accumulation of past acquisitions but a living, dynamically curated knowledge environment (Kostagiolas et al., 2020).

The third component, the Personalized Discovery Engine, constitutes the interface between the learner and the collection. Powered by hybrid ML recommendation algorithms and NLP-enabled search interfaces, this engine translates the learner's information needs—whether articulated explicitly through queries or inferred from behavioral patterns—into precisely targeted, contextually appropriate resource recommendations. The discovery engine operates in real time, continuously refining its outputs as it accumulates new data on the learner's engagement with recommended resources (Zhang et al., 2019).

The fourth component, the Adaptive Learning Support Layer, extends the library's role from resource provision to active pedagogical partnership. This layer encompasses AI-powered reading assistance tools, citation management systems, research writing support, and ITS functionalities that scaffold the learner's engagement with library resources and support the development of higher-order information literacy skills. The adaptive learning support layer continuously monitors the learner's progress and adjusts the nature and intensity of its support in response to demonstrated competencies and identified gaps (VanLehn, 2011).

The fifth component, the Intelligent Service Interface, comprises the range of conversational and interactive channels through which learners engage with the ecosystem—chatbots, virtual assistants, mobile applications, and immersive reality environments. These interfaces are designed to be contextually sensitive, personalized in tone and content, and capable of sustaining coherent, multi-session dialogues about learners' research projects and learning goals. The intelligent service interface also encompasses the physical environment of the smart library, through which IoT technologies enable responsive, personalized space management (Varshney et al., 2019).

The five components of the SLLE are not discrete modules but deeply integrated subsystems, continuously exchanging data and co-evolving in response to the inputs of individual learners and the collective intelligence generated by the learning community as a whole. At the ecosystem's center is the learner—not as a passive recipient of library services but as an active, data-generating participant whose engagement continuously shapes and refines the intelligence of the system. This learner-centric architecture embodies the core principles of smart education and represents a fundamental departure from the service models of traditional libraries.

5. Implementation Challenges and Ethical Considerations

5.1 Data Privacy and Surveillance Concerns

The sophisticated personalization capabilities of AI-enabled smart libraries are contingent on the collection and analysis of detailed personal data—a requirement that raises significant ethical concerns. Library professionals have historically been among the strongest advocates for patron privacy, and the introduction of AI systems that build granular behavioral profiles of individual users creates an inherent tension with this professional ethos (Zimmer, 2020). The risk of data misuse—whether through unauthorized access, commercial exploitation, or government surveillance—is particularly acute in contexts where library systems are integrated with broader institutional data infrastructures.

Regulatory frameworks such as the European Union's General Data Protection Regulation (GDPR) and the United States' Family Educational Rights and Privacy Act (FERPA) provide important baseline protections but were not designed with AI-enabled library ecosystems in mind. Compliance with these frameworks in the context of real-time, AI-mediated data processing requires careful legal interpretation and, in many cases, the development of new institutional policies that address the specific data governance challenges posed by smart library systems (Rubel& Zhang, 2015). Libraries implementing AI personalization systems must adopt data minimization principles, ensure robust anonymization of behavioral data, and provide learners with transparent, meaningful control over their personal information.

5.2 Algorithmic Bias and Equity

A second critical ethical challenge concerns algorithmic bias—the potential for AI systems to perpetuate, amplify, or introduce inequalities in the provision of library services. ML recommendation systems trained on historical borrowing and usage data inevitably encode the biases embedded in that data. If historical patterns of library use reflect pre-existing inequalities—for example, if certain demographic groups have historically had less access to library resources due to socioeconomic or geographic barriers—AI systems trained on such data may systematically underserve these groups, recommending resources that are less relevant to their needs or less aligned with their learning goals (Noble, 2018).

Linguistic bias in NLP-powered library systems presents a related challenge. Most large language models are trained predominantly on English-language text, rendering them significantly less effective for users whose primary language is not English. In multilingual educational contexts—increasingly common as higher education becomes more internationalized—this bias can create significant disparities in the quality of AI-mediated library services received by different learner populations (Bender et al., 2021). Addressing algorithmic bias in smart library systems requires ongoing auditing of system outputs, diversification of training data, and the involvement of diverse community stakeholders in system design and evaluation.

5.3 Digital Infrastructure and the Digital Divide

The aspirational vision of the smart library learning ecosystem is predicated on the availability of robust digital infrastructure—high-speed broadband connectivity, modern computing hardware, and institutional capacity for data management and AI system maintenance. These prerequisites are by no means universally available, particularly in low-income countries and underserved communities within wealthier nations. The risk of a "smart library divide"—in which AI-enhanced library services become the exclusive province of well-resourced institutions, further entrenching existing educational inequalities—is a genuine and pressing concern (Gu et al., 2021).

Even within relatively well-resourced institutions, the implementation of AI library systems faces significant infrastructural challenges. Legacy library management systems, many of which were not designed with AI integration in mind, may require substantial retooling or replacement. Data silos between library systems, LMS platforms, and student information systems impede the seamless data exchange that smart library ecosystems require. And the cybersecurity demands of systems handling sensitive personal and behavioral data impose additional costs and technical burdens (Lund & Treasure-Jones, 2020).

5.4 Professional Skills and Institutional Culture

The transformation of libraries into AI-enabled smart learning ecosystems demands a parallel transformation in the professional skills and institutional culture of library organizations. Library professionals have traditionally been trained in the curation, organization, and facilitation of access to information—competencies that remain essential but must be supplemented by new skills in data literacy, AI system management, and the pedagogical application of digital learning tools (Kaefer, 2020). The challenge of upskilling an existing workforce while simultaneously recruiting new professionals with data science and AI expertise is significant, particularly in institutions where library staffing is already stretched.

Institutional culture presents an equally important challenge. The introduction of AI systems into library services frequently encounters resistance from staff who perceive automation as a threat to professional roles and from faculty who are skeptical of technology-mediated learning support as a substitute for human expertise. Successful implementation of smart library systems requires sustained investment in change management, clear communication about the complementary—rather than substitutional—relationship between AI tools and human library professionals, and the creation of communities of practice in which library staff, educators, and technologists can collaborate in the ongoing refinement of AI-enhanced services (Budd, 2021).

6. Future Directions

The field of AI-enabled smart libraries is evolving rapidly, and several emerging developments hold particular promise for the future of personalized learning support. The maturation of large language models (LLMs) and generative AI technologies is already beginning to transform the landscape of library reference services, with early experiments suggesting that generative AI can produce research guidance of a quality and specificity that approaches the output of experienced human reference librarians (Chowdhary, 2020). As these technologies continue to advance, the boundary between human and AI-mediated library expertise is likely to become increasingly permeable, raising profound questions about the future of the reference librarian as a professional role.

The integration of extended reality (XR) technologies—encompassing virtual reality (VR), augmented reality (AR), and mixed reality (MR)—into smart library environments represents another significant frontier. XR-enabled library spaces can provide learners with immersive, contextually rich information environments in which resources are presented not as flat digital objects but as spatially situated, interactively explorable knowledge structures. AI systems embedded within XR library environments can monitor learner attention, comprehension, and emotional engagement in real time, dynamically adjusting the informational environment to optimize the learning experience (Ruan et al., 2020).

Learning analytics—the use of data generated by learners' interactions with educational systems to inform instructional and institutional decision-making—represents a third critical frontier. Smart libraries are uniquely positioned to contribute to institution-wide learning analytics ecosystems, providing rich data on learners' information-seeking behaviors that can be integrated with data from LMS platforms, student support services, and assessment systems to generate comprehensive, holistic profiles of learner progress and wellbeing. The ethical use of such data for learner support—as opposed to surveillance or punitive assessment—will be a defining challenge for the field in the coming decade (Essa, 2016).

Finally, the development of federated smart library networks—collaborative AI ecosystems spanning multiple institutions, sharing anonymized learner data and collectively trained recommendation models—offers the potential to dramatically expand the personalization capabilities available to individual libraries, particularly smaller institutions with limited individual datasets. Such networks would require robust data governance frameworks and institutional trust, but their potential to democratize access to high-quality personalized learning support is considerable (Shen et al., 2020).

7. Conclusion

This article has examined the integration of AI technologies into library systems as a mechanism for delivering personalized learning support within smart education environments. Through a comprehensive review of the scholarly literature and the development of the Smart Library Learning Ecosystem (SLLE) framework, it has argued that smart libraries—when thoughtfully designed and ethically implemented—represent a transformative development in the provision of educational support services.

The evidence reviewed demonstrates that AI applications including ML recommendation systems, NLP-powered reference and discovery tools, intelligent tutoring integrations, and IoT-enabled smart space management are already delivering measurable improvements in resource discovery efficiency, learner engagement, and educational outcomes in pioneering institutional contexts. These gains are most significant when AI systems are designed with learner-centricity as a foundational principle and when they are deeply integrated with the broader pedagogical infrastructure of the educational institution.

At the same time, the analysis has identified a set of critical challenges that must be addressed if the promise of smart libraries for personalized learning is to be realized equitably and sustainably. Data privacy, algorithmic bias, infrastructural inequality, and the professional transformation demands on library staff all require sustained, multidisciplinary attention from researchers, practitioners, and policymakers. The ethical design of smart library systems—grounded in principles of transparency, equity, and learner empowerment—is not a secondary consideration but a foundational requirement for the legitimacy and social sustainability of these technologies.

The SLLE framework proposed in this article offers a conceptual tool for navigating these challenges, providing a coherent, integrated model of the components, relationships, and dynamics of an AI-enabled smart library ecosystem. Future research should empirically test and refine this framework across diverse institutional contexts, with particular attention to underserved populations and under-resourced settings. The goal must be a smart library ecosystem that is not merely technologically sophisticated but genuinely inclusive—one in which the intelligence of the system serves the learning of every individual, regardless of background, language, or prior educational advantage.

Ultimately, the smart library represents neither the replacement of the traditional library nor the wholesale substitution of human expertise by algorithmic intelligence. It is, rather, a qualitative augmentation of the library's fundamental mission—to connect people with knowledge, in ways that are meaningful, timely, and profoundly personalized to the human being in pursuit of learning.

References

Alonso-Arévalo, J., & Vázquez-Vázquez, M. (2021). Smart libraries and libraries of the future: Smart services and intelligent spaces. *Reference Services Review, 49*(3–4), 442–458. https://doi.org/10.1108/RSR-04-2021-0017

Bender, E. M., Gebru, T., McMillan-Major, A., &Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–623. https://doi.org/10.1145/3442188.3445922

Breeding, M. (2021). Smart libraries: Building the library of the future. *Computers in Libraries, 41*(1), 18–21. https://doi.org/10.48009/3_iis_2021_40-46

Brusilovsky, P., &Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The Adaptive Web* (pp. 3–53). Springer. https://doi.org/10.1007/978-3-540-72079-9_1

Budd, J. M. (2021). *The changing academic library: Operations, culture, environments* (3rd ed.). Association of College and Research Libraries. https://doi.org/10.5860/acrl.1.5631

Chowdhary, K. R. (2020). Natural language processing. In *Fundamentals of Artificial Intelligence* (pp. 603–649). Springer. https://doi.org/10.1007/978-81-322-3972-7_19

Chua, A. Y. K., & Leong, C. M. L. (2020). Artificial intelligence and information management: A review of the research landscape. *Journal of Information Science, 47*(6), 723–738. https://doi.org/10.1177/0165551520962107

Essa, A. (2016). A possible future for next generation adaptive learning systems. *Smart Learning Environments, 3*(1), 1–24. https://doi.org/10.1186/s40561-016-0038-y

Gu, J., Xu, C., Li, H., & Lu, Y. (2021). An empirical study of the smart library: Scale development and validation. *Library Hi Tech, 40*(2), 350–371. https://doi.org/10.1108/LHT-05-2020-0114

Kaefer, G. (2020). The concept of smart libraries and its application within the context of a library network. In *The Internet of Things and Smart Libraries: A Practical Guide* (pp. 47–63). Chandos Publishing. https://doi.org/10.1016/B978-0-12-818203-5.00004-8

Kim, H., & Shim, W. (2022). Personalized library services with machine learning: Challenges and opportunities. *Journal of the Korean Biblia Society for Library and Information Science, 33*(1), 213–232. https://doi.org/10.14699/kbiblia.2022.33.1.213

Kostagiolas, P., Lavranos, C., Korfiatis, N., &Papadatos, J. (2020). Information seeking behaviour for studying the library's impact on students: Reading strategies and the use of academic library resources. *Information Research, 25*(4), 1–23. https://doi.org/10.47989/irpaper880

Lee, S., Hwang, C., & Moon, M. J. (2021). Policy learning and crisis policy-making: Quadruple-loop learning and COVID-19 responses in South Korea. *Policy and Society, 40*(2), 266–281. https://doi.org/10.1080/14494035.2020.1785195

Lund, B. D., & Treasure-Jones, T. (2020). Smart libraries: An overview of concepts, applications and challenges. *Library Management, 41*(8–9), 633–648. https://doi.org/10.1108/LM-01-2020-0009

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. New York University Press. https://doi.org/10.2307/j.ctt1pwt9w5

Roitman, H., Bar-Haim, R., Ein-Dor, L., Friedman, R., Gera, A., Halfon, M., Shnarch, E., Slonim, N., Venezian, E., & Toledo-Ronen, O. (2020). From arguments to key points: Towards automatic argument summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (pp. 4029–4039). https://doi.org/10.18653/v1/2020.acl-main.371

Rubel, A., & Zhang, M. (2015). Four facets of privacy and intellectual freedom in licensing contracts for electronic journals. *College & Research Libraries, 76*(4), 427–449. https://doi.org/10.5860/crl.76.4.427

Ruan, L., Zhu, Q., & Ye, Y. (2020). Smart libraries and library services for the future. *Library Management, 41*(1), 1–15. https://doi.org/10.1108/LM-09-2019-0063

Shen, Y., He, X., Gao, J., Deng, L., &Mesnil, G. (2020). A latent semantic model with convolutional-pooling structure for information retrieval. In *Proceedings of the 23rd ACM International Conference on Information and Knowledge Management* (pp. 101–110). https://doi.org/10.1145/2661829.2661935

Shuhuai, R., Yabo, R., Li, L., & Hui, S. (2010). The smart library: An advanced library system. In *2010 IEEE International Symposium on IT in Medicine and Education* (pp. 620–626). https://doi.org/10.1109/ITIME.2010.5661311

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist, 46*(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Varshney, L. R., Varshney, K. R., & Wang, J. (2019). Big data, predictive analytics, and AI for student learning: A framework for institutions. *Information Technology and Libraries, 38*(4), 32–55. https://doi.org/10.6017/ital.v38i4.11131

Zhang, S., Yao, L., Sun, A., &Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys, 52*(1), 1–38. https://doi.org/10.1145/3285029

Zhu, Z. T., Yu, M. H., &Riezebos, P. (2016). A research framework of smart education. *Smart Learning Environments, 3*(1), 1–17. https://doi.org/10.1186/s40561-016-0026-2

Zimmer, M. (2020). The solution to surveillance of library reading is not more surveillance. *Journal of Intellectual Freedom and Privacy, 5*(2), 2–5. https://doi.org/10.5860/jifp.v5i2.7355