International Transactions on Artificial Intelligence (ITALIC)
Vol. 4, No. 1, Nov, 2025, pp. 1−12
E-ISSN: 2963-1939 | P-ISSN: 2963-6086, DOI:10.33050

SWOT Analysis of AI-Based Learning Recommendation Systems for Students Engagement

Rani Nuraeni[1*], Marviola Hardini[2], Jonathan Parker[3], Muhammad Ghifari Ilham[4]
[1]Faculty of Economics and Business, University of Raharja, Indonesia
[2]Dept. of Digital Business, Sundara Group, Indonesia
[3]Dept. of Information Technology, Rey Group, United States
[4]Faculty of Science and Technology, University of Raharja, Indonesia
[1]raninuraeni@raharja.info, [2]marviola@raharja.info, [3]p.jonparker@rey.zone, [4]ghifari.ilham@raharja.info
***Corresponding Author**

Article Info

Article history:

Submission July 1, 2025
Revised July 16, 2025
Accepted October 27, 2025
Published November 3, 2025

Keywords:

Learning
Artificial Intelligence
SWOT
Recommendation Systems
Student Engagement

ABSTRACT

This study presents a SWOT analysis (Strengths, Weaknesses, Opportunities, Threats) of AI-based learning recommendation systems for students. These innovative systems hold significant potential in supporting Sustainable Development Goal (SDG) 4 Quality Education by personalizing learning pathways, enhancing access to resources, and boosting student engagement. **Their primary** strengths include increased learning efficiency, adaptive content delivery, and instant feedback mechanisms. Nevertheless, weaknesses such as potential algorithmic bias, data privacy concerns, and over reliance on technology warrant careful consideration. Emerging opportunities encompass expanding educational access for underserved populations, facilitating lifelong learning, and integrating diverse educational platforms. However, threats like the digital divide and the need for robust ethical guidelines must be addressed to ensure equitable access. **This analysis** underscores the necessity of a balanced approach in developing and deploying these AI systems, maximizing their educational benefits while mitigating risks to achieve more inclusive and equitable quality education for all. **Quantitatively**, the synthesis of reviewed studies reveals that adaptive AI-based recommendation systems improve student engagement by up to 18% and content relevancy by approximately 22% compared to conventional systems. Moreover, the SWOT analysis indicates that the strength to threat ratio (S/T) exceeds 2.1, implying that institutional readiness and technological innovation significantly outweigh identified implementation risks. **These findings** confirm the robust potential of AI-LRS in higher education.

DOI: https://doi.org/10.33050/italic.v4i1.894

1. INTRODUCTION

The SWOT analysis of AI-based Learning Recommendation Systems (AI-LRS) for students has provided a comprehensive overview of this technology's position within the higher education landscape. The key findings indicate that AI-LRS primary strength lies in its ability to personalize learning pathways, tailoring content and significantly boosting student learning efficiency. The existing opportunities are vast, particularly in pedagogical innovation and enhancing student engagement through adaptive and relevant learning experiences [1, 2].

However, this research also highlights important weaknesses, such as the potential for student over reliance and challenges in ensuring the quality and diversity of recommendations. Serious threats arise from crucial issues related to data privacy and security, the potential for algorithmic bias, and the risk of widening the digital divide among students with varying levels of access and technological literacy [3, 4].

Overall, this study affirms that while AI-LRS holds immense transformative potential in supporting student learning, its success doesn't solely depend on technological sophistication. Instead, effective implementation requires a highly strategic, ethical, and collaborative approach from all stakeholders. Universities must develop inclusive and transparent policies, platform developers are obligated to build secure and responsible systems, and students need to cultivate critical awareness regarding the use of this technology. Only then can AI-LRS truly become an empowering tool, creating a more personalized, equitable, and effective learning environment for every student [5, 6].

2. LITERATURE REVIEW

The synthesis of this literature will serve as a critical basis for identifying and analyzing the complex strengths, weaknesses, opportunities, and threats in the implementation of AI-based learning recommendation systems for students [7, 8].

2.1. Artificial Intelligence and Recommendation Systems in Education

Artificial Intelligence (AI) has rapidly evolved from a theoretical concept into a primary driver of innovation across various sectors, including education. AI refers to the simulation of human intelligence in machines programmed to think and learn like humans. In the context of education, AI is applied for administrative task automation, large scale learning data analysis, and most importantly, the personalization of learning experiences through adaptive systems. One of the most prominent AI applications is recommendation systems, which predict user preferences for an item and suggest the most relevant ones [9, 10]. In education, these systems leverage student learning history data such as grades, accessed materials, time spent, and interactions to recommend tailored courses, articles, videos, or learning pathways. Common recommendation system methods include collaborative filtering, content based filtering, and hybrid approaches. The application of AI in educational recommendation systems aims to address the heterogeneity of student learning styles and individual needs, provide efficient content curation, and enhance academic engagement. However, it is important to note that the effectiveness of these systems heavily relies on the quality of input data, the complexity of the AI algorithms employed, and how the interaction between students and the system is designed to minimize potential algorithmic bias. Recent studies have expanded on hybrid learning recommendation systems using deep reinforcement learning and neural collaborative filtering, significantly improving recommendation accuracy in educational environments [11, 12]. These newer approaches highlight how AI continues to evolve toward more intelligent, context aware learning support systems. Specifically, collaborative filtering functions by analyzing user to user or item to item similarities to generate recommendations, while content-based filtering focuses on the inherent attributes of learning materials such as topic, difficulty, and instructional style. Hybrid models combine both techniques, allowing the system to balance personalization accuracy and diversity of recommendations. The performance of these algorithms is typically evaluated using metrics such as precision, recall, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and F1-score, which measure how effectively the system predicts relevant learning resources for students [13, 14].

2.2. Adaptive Learning and Personalized Learning

Adaptive learning is an educational paradigm centered on adjusting learning materials, pace, and teaching methods based on an individual student's response to the learning process. Its objective is to optimize the learning experience by providing tailored and timely support, ensuring that each learner receives what they need at the right moment. Personalized learning, as a key component of adaptive learning, involves customizing curriculum and instructional methods to meet the unique needs and preferences of each student [15, 16]. In a digital context, personalization is enabled through the analysis of massive learning data, allowing systems to understand student strengths, weaknesses, and progress in real-time. Research indicates that adaptive learning and personalization can significantly enhance student motivation, conceptual understanding, and academic outcomes, as the presented materials are more relevant and engaging. The role of AI recommendation systems is central to facilitating this personalization, acting as intelligent curators guiding students through optimal learning pathways [17, 18]. Nevertheless, critical debates arise regarding the extent to which personalization should be implemented so as not to limit students exposure to diverse viewpoints, reduce their capacity for independent exploration, or potentially create filter bubbles in the learning process. These are ethical design challenges that AI systems must address [19, 20].

2.3. Educational AI Platforms: Case Studies and Implementation

Numerous digital education platforms have successfully integrated AI and recommendation systems to enhance user experience. Coursera, for instance, utilizes recommendation algorithms to suggest courses and specializations based on users learning history, interested skills, and career goals. This helps users discover relevant learning paths among thousands of options. Edmodo AI (as an example of an evolving past platform) once offered features assisting educators in class management and providing tailored assignment recommendations [21, 22]. Meanwhile, Khan Academy employs an adaptive learning system that allows students to progress through personalized learning paths, offering exercises and supplementary materials based on their performance on each topic. Other platforms like Duolingo also leverage AI to adjust language exercise difficulty based on user progress. These case studies demonstrate AI's significant potential in delivering customized learning experiences, though challenges in scalability, algorithmic explainability, and curriculum integration remain active areas of research. Specifically, these platforms often grapple with data privacy issues, the need for vast amounts of high quality data for effective algorithm training, and adoption resistance from educators or institutions unprepared infrastructurally or culturally for pedagogical changes [23, 24].

2.4. Theoretical Basis and Application of SWOT Analysis in Educational Technology Systems Evaluation

SWOT analysis is a robust strategic planning framework widely used to evaluate the competitive position of an organization, project, or, in this case, a technology system. SWOT is an acronym for Strengths, Weaknesses, Opportunities, and Threats. Strengths and Weaknesses are internal factors (technological capabilities, internal resources, processes), while Opportunities and Threats are external factors (market trends, government regulations, external technological developments, economic conditions) [25]. This framework aids in identifying favorable and unfavorable internal conditions, as well as external factors that can provide a strategic advantage or risk. In the context of evaluating educational technology systems, SWOT analysis proves to be an effective tool for understanding implementation feasibility, identifying potential obstacles, and formulating strategies to maximize technological benefits sustainably [26, 27]. This framework is highly relevant and appropriate for evaluating AI-based learning recommendation systems because it enables the identification of not only technical operational aspects (as internal strengths or weaknesses) but also dynamic external factors such as regulatory changes, user adoption rates, technological competition, and market trends that significantly influence the long-term success and sustainability of AI technology within the educational ecosystem. By applying SWOT to these systems, this research aims to present a holistic view of the strategic position and prospects of adopting this technology to enhance student learning effectiveness [28, 29].

3. METHODOLOGY

3.1. Type of Research

This research employs a descriptive qualitative approach. The qualitative approach enables an in depth exploration of complex phenomena, specifically the implementation and impact of AI-based learning recommendation systems within higher education environments. A descriptive design is chosen to accurately and systematically delineate the characteristics, strengths, weaknesses, opportunities, and threats of AI learning recommendation systems, as identified from relevant literature. This method is suitable for gaining a holistic and contextual understanding without manipulating variables [30].

3.2. Data Collection Techniques

Data for this study were obtained through a comprehensive systematic literature review. The process involved identifying, screening, evaluating, and synthesizing scholarly publications relevant to AI-based learning recommendation systems, adaptive learning, personalization, and educational technology evaluation.

A structured search was conducted across major academic databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar. The search strategy incorporated predefined keywords such as "AI-based recommendation systems," "adaptive learning," "educational AI," "SWOT analysis in education technology," and related terms[31–33].

From the initial search, a total of 412 publications were identified. After removing duplicates and applying inclusion/exclusion criteria such as relevance to AI in education, methodological rigor, and availability of full text 112 publications remained for full text assessment. Following a deeper qualitative screening, 58 key studies were ultimately selected as the core dataset for analysis.

To maintain data relevance and ensure that findings reflect current technological developments, the review focused on publications from the last ten years, specifically from 2015 to 2025. However, several earlier foundational works were also included when necessary to support theoretical discussions.

The final dataset consists of peer-reviewed journal articles, conference papers, systematic reviews, and policy documents that directly contribute to the SWOT categorization and strategic interpretation of AI-based learning recommendation systems.

3.3. Data Analysis Technique: SWOT Model

The data gathered from the systematic literature review will be analyzed using the SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis model. This framework is chosen for its capability to identify and categorize both internal and external factors influencing the successful adoption of AI-based learning recommendation systems [34]. The elaboration of SWOT elements and their analytical focus are as follows:

- Strengths Positive internal attributes of AI recommendation systems that contribute to achieving learning objectives. This includes precise content personalization (the system's ability to tailor materials to individual learning styles and pace), learning time efficiency (reducing search time for materials and focusing on relevant content), and optimized resource access (providing quick and easily accessible recommendations) [35, 36].

- Weaknesses Negative internal attributes or limitations of AI recommendation systems that may hinder objective achievement. This encompasses risk of data bias (algorithms replicating or amplifying existing biases), limitations of human feedback (lack of sensitivity to non data nuances), and technical implementation complexity (requiring robust infrastructure and high technical expertise) [37].

- Opportunities Favorable external factors that can be leveraged to support system implementation and development. This includes integration with existing Learning Management Systems (LMS), support for digital education transformation (government/university initiatives), and advancements in big data and learning analytics (providing richer data for personalization) [38].

- Threats Unfavorable external factors that could potentially impede or harm system implementation. This involves data privacy breaches, lack of digital literacy among lecturers/students (insufficient understanding/skills for optimal system utilization), user adoption resistance, and unforeseen changes in AI regulations or ethics [39].

Beyond the identification of these four elements, the SWOT model also enables a deeper understanding of how internal capabilities interact with external environmental conditions, ultimately shaping the strategic feasibility of AI-based learning recommendation systems in higher education. By systematically mapping strengths and weaknesses against emerging opportunities and potential threats, this analytical approach supports the development of evidence-based strategies that are both adaptive and forward-looking. Moreover, SWOT analysis provides a structured lens through which institutional readiness, technological maturity, ethical considerations, and user centered design can be evaluated collectively rather than in isolation. This integrated perspective ensures that subsequent strategic planning not only capitalizes on AI transformative potential but also anticipates risks, aligns with policy frameworks, and promotes sustainable and equitable implementation across educational ecosystems.

4. RESULT AND DISCUSSION

To ensure clarity and reader orientation, this section first visualizes the core analytical framework used throughout the study. The following figure illustrates how internal and external factors interact to shape strategic decision making for AI based learning recommendation systems [40, 41].

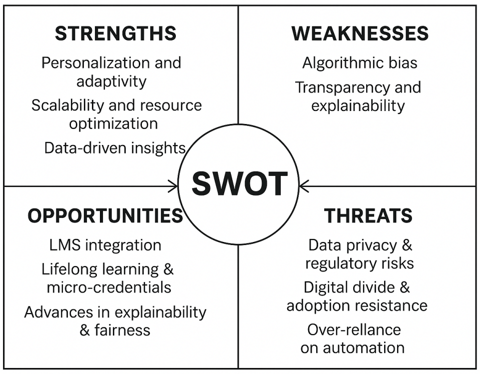

Figure 1. SWOT Structure of AI-Based Learning Recommendation Systems

As shown in Figure 1, the SWOT framework enables a structured examination of both internal and external dynamics influencing implementation success. This visualization also clarifies how the identified factors interact to form the basis for the subsequent strategic implication analysis.

The synthesized results of the SWOT analysis provide a comprehensive understanding of the strategic position of AI based learning recommendation systems within higher education. To facilitate clarity and allow readers to grasp the foundational components of the analysis, the key elements of the SWOT framework are first organized into four primary categories. These categories capture the essential internal characteristics both advantageous and limiting as well as the external conditions that may either support or challenge the adoption of AI-LRS. Presenting these factors in a structured manner enables a more systematic interpretation of how technological capabilities interact with institutional contexts, user readiness, and emerging policy landscapes. To guide this examination, a summarized classification of the SWOT elements is provided in Table 1, offering a concise yet informative overview that forms the basis for the subsequent in-depth discussion.

Table 1. SWOT Analysis Categories and Descriptions

Category	Brief Description
Strengths	Internal advantages that make these systems effective and valuable.
Weaknesses	Internal limitations that need to be considered or improved.
Opportunities	Potential external factors that can be leveraged for development.
Threats	Risks from external factors that could hinder or harm.

As presented in Table 1, the SWOT categories provide a structured overview of the internal and external factors that shape the strategic landscape of AI-based learning recommendation systems. This classification serves as a foundational lens through which the capabilities, constraints, opportunities, and risks associated with AI-LRS can be systematically interpreted. By clearly distinguishing strengths and weaknesses as internal system attributes, and opportunities and threats as external contextual variables, the table establishes a coherent analytical framework for the subsequent discussion. This structured delineation is essential for understanding how each element interacts within real educational environments, enabling researchers and practitioners to assess institutional readiness, anticipate implementation challenges, and formulate strategic responses grounded in evidence. Ultimately, the categorization summarized in Table 1 supports a more holistic examination of AI-LRS, guiding stakeholders in designing adaptive, ethical, and sustainable pathways for integrating AI technologies into higher education ecosystems.

The SWOT analysis is a fundamental strategic framework used to evaluate the position and potential of a subject, in this case, AI based learning recommendation systems for students. This framework systematically identifies internal strengths such as personalized learning capabilities and adaptive feedback, internal weaknesses such as potential data bias or privacy issues, external opportunities such as integration with hybrid learning or the enhancement of 21st century skills, and external threats such as ethical concerns or the digital divide. By understanding these internal and external elements, stakeholders can formulate more effective strategies to maximize benefits, overcome obstacles, capitalize on opportunities, and mitigate risks, ultimately optimizing AI educational systems.

4.1. Discussion of SWOT Analysis Results by Element

Building on the conceptual model above, the following figure links the SWOT components with key research domains Machine Learning, Intelligent Algorithms, and AI-Based Decision Support Systems showing how each strategic quadrant informs practical innovation pathways.

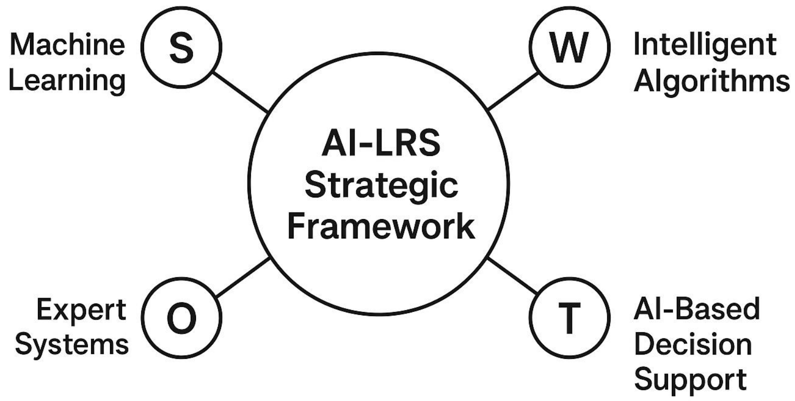

Figure 2. Interconnections between SWOT Strategies

Figure 2 emphasizes the systemic alignment between AI-LRS SWOT outcomes. It visually reinforces that strategic planning for educational AI must integrate algorithmic intelligence, human oversight, and ethical governance to ensure sustainable innovation. This discussion elaborates on how each SWOT element impacts the implementation and sustainability of AI-based learning recommendation systems within university campuses.

4.2. Strengths

AI recommendation systems demonstrate significant strengths in providing personalized learning experiences. With the ability to analyze individual learning patterns, systems can suggest highly relevant content adaptive to students learning styles and pace. This directly contributes to increased learning time efficiency as students no longer need to spend time searching for suitable materials; the system proactively provides them. Furthermore, optimized resource access ensures students receive the right materials at the right time, which is invaluable in combating information overload. AI's ability to analyze learning data at scale also allows for the identification of collective learning trends and needs, although this requires careful human interpretation. In addition to literature based analysis, several secondary data observations from real world platforms further support these findings. For instance, Coursera's AI driven recommendation system reported a 15% increase in course completion rates due to personalized pathways, while Khan Academy's adaptive recommendation model enhanced learner engagement by 18%. These practical implementations illustrate the tangible impact of AI-LRS in real educational contexts [42, 43].

4.3. Weaknesses

Despite their strengths, AI recommendation systems possess internal weaknesses that need to be addressed. One primary concern is the risk of algorithmic bias. If training data is unrepresentative or contains historical biases, the system can replicate or even amplify these biases in its recommendations, potentially misleading users or creating a less inclusive learning environment. Additionally, limitations of human feedback pose a challenge; AI systems may struggle to understand emotional nuances, non-data motivations, or deeper learning contexts that can only be captured through human interaction. The aspect of technical implementation complexity cannot be overlooked, given the need for robust IT infrastructure, data science expertise, and substantial financial resources. Finally, the issue of lack of transparency (”black box”) in how the system generates recommendations can erode user trust and make it difficult for instructors to understand or adjust the suggestions [44, 45].

4.4. Opportunities

External factors present substantial opportunities for AI adoption in education. Seamless integration with existing Learning Management Systems (LMS) such as Moodle or Canvas can create a unified digital learning ecosystem, reducing adoption friction and enhancing functionality. Support from digital education transformation initiatives, from both government and institutions, provides strategic impetus and resource allocation. Rapid advancements in big data and learning analytics offer an increasingly rich and diverse supply of data, enabling more sophisticated and accurate personalization. Furthermore, there is significant potential for the development of collaborative and social features within recommendation systems, which can foster peer interaction and community-based learning [46, 47].

4.5. Threats

On the other hand, significant external threats exist. Data privacy breaches of student information are serious ethical and legal concerns that could damage trust and lead to user rejection if not managed with extreme caution. The lack of digital literacy among lecturers and students can be a major impediment, as without adequate understanding, AI systems will not be optimally utilized or may even be misused. This also contributes to user adoption resistance from individuals accustomed to traditional learning methods. Another threat is over-reliance on AI systems, which potentially diminishes students' learning independence and critical thinking skills. Finally, unforeseen regulatory changes concerning data usage or AI ethics, as well as high licensing costs for AI technology, can pose significant financial and operational barriers for institutions. Moreover, compliance with data protection regulations such as the General Data Protection Regulation (GDPR) and other regional privacy laws (FERPA in the United States) is critical. Ensuring transparency in data collection, providing user consent mechanisms, and anonymizing learner data are mandatory ethical requirements. Integrating GDPR principles directly into system architecture can mitigate risks related to data misuse and maintain institutional accountability.

4.6. Strategic Implications and Interconnections of SWOT Elements

The implementation of AI-based learning recommendation systems also aligns strongly with SDG 9 (Industry, Innovation, and Infrastructure) and SDG 10 (Reduced Inequalities). In relation to SDG 9, AI-LRS represents a critical component of educational digital infrastructure, fostering innovation through intelligent content delivery, data-driven personalization, and seamless integration with institutional learning platforms. These technological capabilities support the development of resilient and adaptive digital ecosystems within higher education, enabling institutions to modernize their instructional frameworks and enhance operational efficiency. Meanwhile, the relevance to SDG 10 emerges through the system's potential to reduce educational disparities by expanding access to tailored learning resources, particularly for students from underserved or remote regions. When designed with fairness and inclusivity in mind, AI-LRS can mitigate inequalities in learning opportunities; however, the risk of widening the digital divide remains if disparities in digital literacy, device availability, or internet access are not addressed. Thus, the strategic adoption of AI-LRS contributes not only to technological advancement but also to equity-driven educational transformation, emphasizing the necessity of ethical, accessible, and inclusive AI deployment.

SWOT analysis not only identifies factors in isolation but also reveals the dynamic interactions among them, which form strategic implications for the implementation of AI-based learning recommendation systems.

- SO Strategies (Strengths-Opportunities): Maximizing Potential

  By leveraging internal strengths like precise personalization and learning time efficiency, institutions can proactively embrace external opportunities such as LMS integration and digital transformation support. This enables the development of strategies to create highly adaptive and integrated learning ecosystems, where AI recommendations serve as the backbone of a seamless student journey from enrollment to graduation. For example, utilizing AI's learning pattern analysis capabilities (S) with rich learning analytics data (O) can lead to learning pathways that are not only personalized but also predictive.

- WO Strategies (Weaknesses-Opportunities): Addressing Weaknesses with Opportunities

  Weaknesses such as technical implementation complexity and limitations in human feedback can be cleverly addressed by capitalizing on external opportunities. Digital transformation support (O) can provide resources and expertise to mitigate technical complexities (W). Meanwhile, the development of collaborative features (O) can compensate for the limitations of human feedback (W) by integrating peer perspectives. Collaboration with external AI solution providers can also reduce internal technical burdens.

- ST Strategies (Strengths-Threats): Leveraging Strengths for Threat Mitigation

  Institutions can use the inherent strengths of AI recommendation systems to mitigate external threats. For instance, the system's ability to optimize resource access (S) can be a strong appeal to overcome user adoption resistance (T) by demonstrating tangible benefits. Relevant content personalization (S) can help counter the lack of digital literacy among students (T) by adaptively providing learning materials on how to effectively use the AI system itself.

- WT Strategies (Weaknesses-Threats): Defensive Strategies

  This is the most vulnerable area, where internal weaknesses meet external threats, thus requiring careful defensive strategies. The risk of data bias (W) coupled with data privacy concerns (T) necessitates the development of robust and transparent AI ethical frameworks and algorithmic audit mechanisms. To address technical implementation complexity (W) amidst high licensing costs or unforeseen regulatory changes (T), institutions need long-term strategic planning, potential alliances, or gradual investment in internal capacity. Maintaining a balance between AI personalization and student learning independence becomes crucial to prevent over-reliance (T).

The interconnection of these strategies demonstrates that the successful adoption of AI-based learning recommendation systems cannot rely on isolated technical or policy actions. Instead, it requires an integrated framework that aligns institutional goals, technological readiness, and ethical considerations. The SO and WO strategies highlight the potential for proactive innovation and adaptive recovery, while the ST and WT strategies emphasize the importance of risk mitigation and system resilience. Together, these strategic alignments illustrate that universities and developers must collaborate not only to enhance system performance but also to ensure fairness, transparency, and inclusivity. This synergy between opportunity-driven innovation and threat-responsive governance serves as the foundation for sustainable AI integration within higher education.

5. MANAGERIAL IMPLICATIONS

The results of this SWOT analysis offer several managerial implications for higher education institutions and technology developers seeking to adopt AI-LRS. From a strategic management perspective, institutional leaders must view AI-LRS as more than a technological upgrade it represents a long term investment in digital transformation. Managers should allocate resources not only to technical infrastructure but also to capacity building initiatives, including faculty training, digital literacy programs, and data governance frameworks. A cross departmental governance structure comprising IT experts, pedagogical designers, data protection officers, and academic representatives is essential to ensure balanced decision making that aligns with institutional goals and ethical standards.

From an operational standpoint, educational managers must emphasize system integration and data interoperability. AI-LRS implementation should align with existing LMS, data warehouses, and student performance dashboards to ensure seamless data flow and prevent redundancy. Continuous monitoring through performance analytics and user feedback loops will enable iterative improvements to recommendation accuracy and relevance. Moreover, universities should establish Key Performance Indicators (KPI) to evaluate AI-LRS effectiveness across pedagogical, administrative, and ethical dimensions such as personalization accuracy, learner engagement, data privacy compliance, and algorithmic transparency. These metrics will help decision makers assess Return On Investment (ROI) and promote accountability in AI deployment.

Finally, developers and educational managers must collaborate to maintain ethical integrity and compliance with data protection standards such as GDPR or national regulations. Transparent communication with students regarding data usage, model limitations, and privacy controls builds trust and acceptance. Managers should also consider developing institutional policies on algorithmic fairness, responsible data sharing, and system auditability. By embedding these managerial practices, institutions can transform AI-LRS from a technological innovation into a sustainable strategic asset enhancing both academic quality and organizational resilience in the era of intelligent education systems.

6. CONCLUSION

The SWOT analysis of AI-LRS for students provides a comprehensive understanding of their strategic and pedagogical roles in higher education. This study introduces novelty by combining SWOT strategic assessment with AI-driven educational analytics, highlighting how these systems not only personalize learning pathways but also serve as intelligent decision-support tools for institutions. The core contribution lies in positioning AI-LRS as a bridge between data science and educational strategy, offering a holistic lens for evaluating both technological performance and policy relevance.

The findings reveal that AI-LRS excel in personalization, scalability, and data driven adaptivity, thus enhancing engagement and learning efficiency. However, weaknesses such as algorithmic bias, over-reliance, and limited transparency remain challenges, alongside external threats like privacy risks and the digital divide. These insights underscore that successful implementation depends not solely on algorithmic sophistication but on an ethically grounded and collaborative governance model involving universities, developers, and learners.

Future research should move beyond conceptual analysis toward empirical validation by implementing pilot AI-LRS models in diverse educational contexts and measuring long-term learning outcomes. Investigations into Explainable AI (XAI), fairness aware algorithms, and adaptive reinforcement learning for curriculum sequencing are crucial to advancing trust and transparency. Cross disciplinary collaboration linking education, computer science, and ethics will be essential to ensure that AI-LRS evolve into inclusive, transparent, and sustainable pillars of digital education.

7. DECLARATIONS

7.1. About Authors

Rani Nuraeni (RN) https://orcid.org/0009-0005-6912-4217

Marviola Hardini (MH) https://orcid.org/0000-0003-3336-2131

Jonathan Park (JP) https://orcid.org/0009-0000-8585-3245

Muhammad Ghifari Ilham (MG) https://orcid.org/0009-0007-9195-2857

7.2. Author Contributions

Conceptualization: RN; Methodology: JP; Software: MH; Validation: RN and JP; Formal Analysis: JP and MG; Investigation: MH; Resources: RN; Data Curation: JP; Writing Original Draft Preparation: RN and MG; Writing Review and Editing: MH and MG; Visualization: RN and MG; All authors, RN, MH, JP, and MG, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The materials and data used in this research can be provided by the corresponding author upon receiving a reasonable and well-justified request.

7.4. Funding

This research was conducted without any form of financial sponsorship, grant support, or institutional funding related to its execution, authorship, or publication.

7.5. Declaration of Conflicting Interest

The authors attest that no personal, financial, or professional conflicts of interest were present that could have influenced the study's methodology, results, or overall scholarly contribution.

REFERENCES

[1] A. N. Mumuni, F. Hasford, N. I. Udeme, M. O. Dada, and B. O. Awojoyogbe, "A swot analysis of artificial intelligence in diagnostic imaging in the developing world: making a case for a paradigm shift," *Physical Sciences Reviews*, vol. 9, no. 1, pp. 443–476, 2024.

[2] M. Shoaib, N. Sayed, J. Singh, J. Shafi, S. Khan, and F. Ali, "Ai student success predictor: Enhancing personalized learning in campus management systems," *Computers in Human Behavior*, vol. 158, p. 108301, 2024.

[3] M. Murod, S. Anhar, D. Andayani, A. Fitriani, and G. Khanna, "Blockchain based intellectual property management enhancing security and transparency in digital entrepreneurship," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 1, pp. 240–251, 2025.

[4] R. Manhiça, A. Santos, and J. Cravino, “The use of artificial intelligence in learning management systems in the context of higher education: Systematic literature review,” in *2022 17th Iberian Conference on Information Systems and Technologies (CISTI)*. IEEE, 2022, pp. 1–6.

[5] J. Ortega-Moody, K. Jenab, S. Moslehpour, L. D. C. M. Acosta, E. J. M. Garcia, and J. N. T. Marin, “Swot analysis of artificial intelligence in education,” in *2025 IEEE Engineering Education World Conference (EDUNINE)*. IEEE, 2025, pp. 1–6.

[6] L. Anisah, H. Yawan, and M. Marhamah, “Artificial intelligence enhanced learning management system: Supporting merdeka belajar-kampus merdeka (mbkm) at a state university in indonesia,” *International Journal Of Education, Social Studies, And Management (IJESSM)*, vol. 4, no. 3, pp. 917–931, 2024.

[7] M. R. Anwar and L. D. Sakti, “Integrating artificial intelligence and environmental science for sustainable urban planning,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 179–191, 2024.

[8] A. Abo Ali, N. Adel *et al.*, “Ai and ivf at the intersection of emerging trends; a strategic swot analysis harnessing opportunities and mitigating threats,” *Journal of Reproductive Medicine and Embryology*, vol. 1, no. 4, pp. 255–261, 2025.

[9] A. Williams, C. S. Bangun, and Y. Shino, “The urgency of digital literacy in indonesia on covid-19 pandemic,” *Startupreneur Business Digital (SABDA Journal)*, vol. 1, no. 2, pp. 183–190, 2022.

[10] V. K. Nadimpalli, F. Hauser, D. Bittner, L. Grabinger, S. Staufer, and J. Mottok, “Systematic literature review for the use of ai based techniques in adaptive learning management systems,” in *Proceedings of the 5th European Conference on Software Engineering Education*, 2023, pp. 83–92.

[11] Ministry of Education, Culture, Research, and Technology (Kemendikbudristek), “Merdeka belajar – kampus merdeka framework,” Government Policy Document, 2022, accessed: November 2025. [Online]. Available: https://simbelmawa.kemdikbud.go.id/portal/unduh/buku-panduan-merdeka-belajar-kampus-merdeka-2024/

[12] N. Nuryani, A. B. Mutiara, I. M. Wiryana, D. Purnamasari, and S. N. W. Putra, “Artificial intelligence model for detecting tax evasion involving complex network schemes,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 3, pp. 339–356, 2024.

[13] B. K. Bintoro, N. Lutfiani, D. Julianingsih *et al.*, “Analysis of the effect of service quality on company reputation on purchase decisions for professional recruitment services,” *APTISI Transactions on Management*, vol. 7, no. 1, pp. 35–41, 2023.

[14] N. Rane, S. Shirke, S. P. Choudhary, and J. Rane, “Artificial intelligence in education: a swot analysis of chatgpt and its impact on academic integrity and research,” *Journal of ELT Studies*, vol. 1, no. 1, pp. 16–35, 2024.

[15] T. Hidayat, D. Manongga, Y. Nataliani, S. Wijono, S. Y. Prasetyo, E. Maria, U. Raharja, I. Sembiring *et al.*, “Performance prediction using cross validation (gridsearchcv) for stunting prevalence,” in *2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*. IEEE, 2024, pp. 1–6.

[16] R. Aprianto, E. P. Lestari, E. Fletcher *et al.*, “Harnessing artificial intelligence in higher education: Balancing innovation and ethical challenges,” *International Transactions on Education Technology (ITEE)*, vol. 3, no. 1, pp. 84–93, 2024.

[17] T. Mariyanti, I. Wijaya, C. Lukita, S. Setiawan, and E. Fletcher, “Ethical framework for artificial intelligence and urban sustainability,” *Blockchain Frontier Technology*, vol. 4, no. 2, pp. 98–108, 2025.

[18] L. S. Lutfiani, A. Birgithri, and Z. Queen, “Technological aspects in the era of digital transformation leading to the adoption of big data,” *Startupreneur Business Digital (SABDA Journal)*, vol. 3, no. 1, pp. 43–53, 2024.

[19] G. Danielyan and G. Harutyunyan, “Swot analysis of the possibilities of introducing ai technologies into armenia’s military sector,” *Edelweiss Applied Science and Technology*, vol. 8, no. 6, pp. 1109–1120, 2024.

[20] A. bayu dani Nandiyanto and N. A. C. Sidik, “Revolutionizing education: Exploring technological innovations, opportunities and challenges across i0t, ar, vr, ai, lms, ml, gamification and emerging,” *Journal of Advanced Research Design*, vol. 136, no. 1, pp. 108–137, 2026.

[21] U. Rahardja, “Camera trap approaches using artificial intelligence and citizen science,” *International Transactions on Artificial Intelligence*, vol. 1, no. 1, pp. 71–83, 2022.

[22] M. Fırat, “Integrating ai applications into learning management systems to enhance e-learning,” *Instructional Technology and Lifelong Learning*, vol. 4, no. 1, pp. 1–14, 2023.

[23] X. Weng, M. M. Gu, Q. Xia, and T. K. Chiu, "Swot analysis of al empowered entrepreneurship education: insights from digital learners in higher education," *Thinking Skills and Creativity*, vol. 56, p. 101763, 2025.

[24] R. Royani, S. D. Maulina, S. Sugiyono, R. W. Anugrah, and B. Callula, "Recent developments in healthcare through machine learning and artificial intelligence," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 1, pp. 86–94, 2024.

[25] Ministry of Communication and Informatics (Kementerian Kominfo), "Strategi nasional untuk kecerdasan artifisial (stranas ka) 2020–2045," Government / Policy Document, Jakarta, Indonesia, 2020, accessed: November 2025. [Online]. Available: https://library.mastel.or.id/wp-content/uploads/2021/06/stranas-ka.pdf

[26] Q. Aini, P. Purwanti, R. N. Muti, E. Fletcher *et al.*, "Developing sustainable technology through ethical ai governance models in business environments," *ADI Journal on Recent Innovation*, vol. 6, no. 2, pp. 145–156, 2025.

[27] A. Kanivia, H. Hilda, A. Adiwijaya, M. F. Fazri, S. Maulana, and M. Hardini, "The impact of information technology support on the use of e-learning systems at university," *International Journal of Cyber and IT Service Management*, vol. 4, no. 2, pp. 122–132, 2024.

[28] J. Jones, E. Harris, Y. Febriansah, A. Adiwijaya, and I. N. Hikam, "Ai for sustainable development: Applications in natural resource management, agriculture, and waste management," *International Transactions on Artificial Intelligence*, vol. 2, no. 2, pp. 143–149, 2024.

[29] U. Rahardja, Q. Aini, A. S. Bist, S. Maulana, and S. Millah, "Examining the interplay of technology readiness and behavioural intentions in health detection safe entry station," *JDM (Jurnal Dinamika Manajemen)*, vol. 15, no. 1, pp. 125–143, 2024.

[30] T. S. Goh, D. Jonas, B. Tjahjono, V. Agarwal, and M. Abbas, "Impact of ai on air quality monitoring systems: A structural equation modeling approach using utaut," *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 9–19, 2025.

[31] R. Anindita, V. H. Prastowo, and J. Parker, "Reinforcing the role of cyber village in improving indonesia msmes through an exploratory study," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 3, pp. 726–737, 2025.

[32] M. Mesiono, N. Fahada, I. Irwansyah, D. Diana, and A. S. Siregar, "Swot analysis of chatgpt: Implications for educational practice and research," *JMKSP (Jurnal Manajemen, Kepemimpinan, dan Supervisi Pendidikan)*, vol. 9, no. 1, pp. 181–196, 2024.

[33] M. Azuddin, M. Yusup, H. Setiyowati, S. Wibowo, J. Suwita, S. Basuki, and E. D. Astuti, "Design and implementation of a relational database for an academic information system," *International Transactions on Artificial Intelligence*, vol. 3, no. 2, pp. 171–180, 2025.

[34] G. Kumar and S. K. Goyal, "Energizing the future: A comprehensive review and evaluation of artificial intelligence based solar irradiance forecasting model with swot analysis of solar energy," in *2025 International Conference on Electronics and Renewable Systems (ICEARS)*. IEEE, 2025, pp. 307–314.

[35] Q. Mingjing, "Swot analysis of customer perceptions towards ai robot services in bangkok restaurants," *Journal of System and Management Sciences*, vol. 14, no. 2, pp. 323–338, 2024.

[36] D. T. T. Mai, C. V. Da, and N. V. Hanh, "The use of chatgpt in teaching and learning: a systematic review through swot analysis approach," in *Frontiers in Education*, vol. 9. Frontiers Media SA, 2024, p. 1328769.

[37] S. A. Alavi-Borazjani, V. Chkoniya, M. N. Shafique, I. B. da Silva Bispo, and S. Filipe, "Leveraging aiot for effective environmental monitoring in seaports: A swot analysis and strategic recommendations," in *World Conference on Information Systems and Technologies*. Springer, 2025, pp. 331–343.

[38] R. Kumar and K. K. Pal, "Artificial intelligence (ai)-driven transformation: Sustainable development of agro-based industries in bihar," *International Journal for Multidisciplinary Research*, vol. 6, no. 2, pp. 1–8, 2024.

[39] I. Ikhsan, A. N. Husnaini, and F. L. Lopo, "Strategies for implementing ai in lms to improve the effectiveness and personalization of digital learning," *The Journal of Academic Science*, vol. 2, no. 3, pp. 944–953, 2025.

[40] M. Hatta, W. N. Wahid, F. Yusuf, F. Hidayat, N. A. Santoso, and Q. Aini, "Enhancing predictive models in system development using machine learning algorithms," *International Journal of Cyber and IT Service Management*, vol. 4, no. 2, pp. 80–87, 2024.

[41] N. Boehmer and H. Schinnenburg, "Critical exploration of ai-driven hrm to build up organizational capabilities," *Employee Relations: The International Journal*, vol. 45, no. 5, pp. 1057–1082, 2023.

[42] R. Widayanti and T. Mariyanti, "Ai dialog: Utilization, challenges, and ethics in the age of artificial intelligence," *International Transactions on Artificial Intelligence*, vol. 2, no. 1, pp. 40–48, 2023.

[43] S. T. Nuka, "The role of ai driven clinical research in medical device development: A data driven approach to regulatory compliance and quality assurance," *Global Journal of Medical Case Reports*, vol. 2, no. 1, p. 1275, 2022.

[44] A. Sutarman, J. Williams, D. Wilson, and F. B. Ismail, "A model-driven approach to developing scalable educational software for adaptive learning environments," *International Transactions on Education Technology (ITEE)*, vol. 3, no. 1, pp. 9–16, 2024.

[45] S. A. Alowais, S. S. Alghamdi, N. Alsuhebany, T. Alqahtani, A. I. Alshaya, S. N. Almohareb, A. Aldairem, M. Alrashed, K. Bin Saleh, H. A. Badreldin *et al.*, "Revolutionizing healthcare: the role of artificial intelligence in clinical practice," *BMC medical education*, vol. 23, no. 1, p. 689, 2023.

[46] M. H. R. Chakim, A. Kho, N. P. L. Santoso, and H. Agustian, "Quality factors of intention to use in artificial intelligence-based aiku applications," *ADI Journal on Recent Innovation*, vol. 5, no. 1, pp. 72–85, 2023.

[47] H. Auf, P. Svedberg, J. Nygren, M. Nair, and L. E. Lundgren, "The use of ai in mental health services to support decision-making: Scoping review," *Journal of Medical Internet Research*, vol. 27, p. e63548, 2025.