International Journal of Integrated Research and Practice (IJIRP)

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

AI-Driven Personalization in Learning: Impacts on Student Engagement

Dr. Ritesh Mishra
Associate Professor
MATS, School of Education
MATS, University, Raipur Chhattisgarh

Abstract

With the embedded Artificial Intelligence (AI) in the education process, the potentials of the learning process to be personalized are borne. This research paper looks at how individualization with the use of AI can enhance student participation in any learning environment. The poorly designed instructional practices usually fail to meet the needs of individual learners in the aspects of motivation, participation, and academic performances. Through data analytics, adjustable algorithms, and intelligent feedbacks, though, AI-powered systems would be able to tailor the nature of content, pace, and learning pathway to each student in a way that meets his/her preferences and levels.

In the paper, the researcher presents a critical examination of the effects that AI-driven personalization have on measures of engagement such as attention, motivation, participation, and academic success. It provides a direction into real-life applications including adaptive learning systems, intelligent tutoring systems, recommendation system, and live analysis that could be used to transform the learning environments into more inclusive and responsive systems. In addition, the paper indicates the potential future of AI in meeting the different needs of learners such as learners with learning disabilities or low access to standard learning resources.

Although the virtues of AI in enhancing closer interaction are quite conspicuous, the study also points out important issues. Such concerns as privacy of data, bias of algorithms, online access disparities, and the danger of excessive dependence on technology also open the way to serious limitations to its adoption at large. Making sure that AI applications support, but do not substitute human educators is also necessary to ensure their sustainable implementation.

On balance, the results indicate that personalization based on AI can transform how students engage with learning content and represent a channel to more equitable, encouraging, and efficient education systems. Striking the right balance between innovation and ethical considerations, stakeholders will be able to use AI in order to unlock a higher tier of student engagement and academic success in the 21st -century classroom.

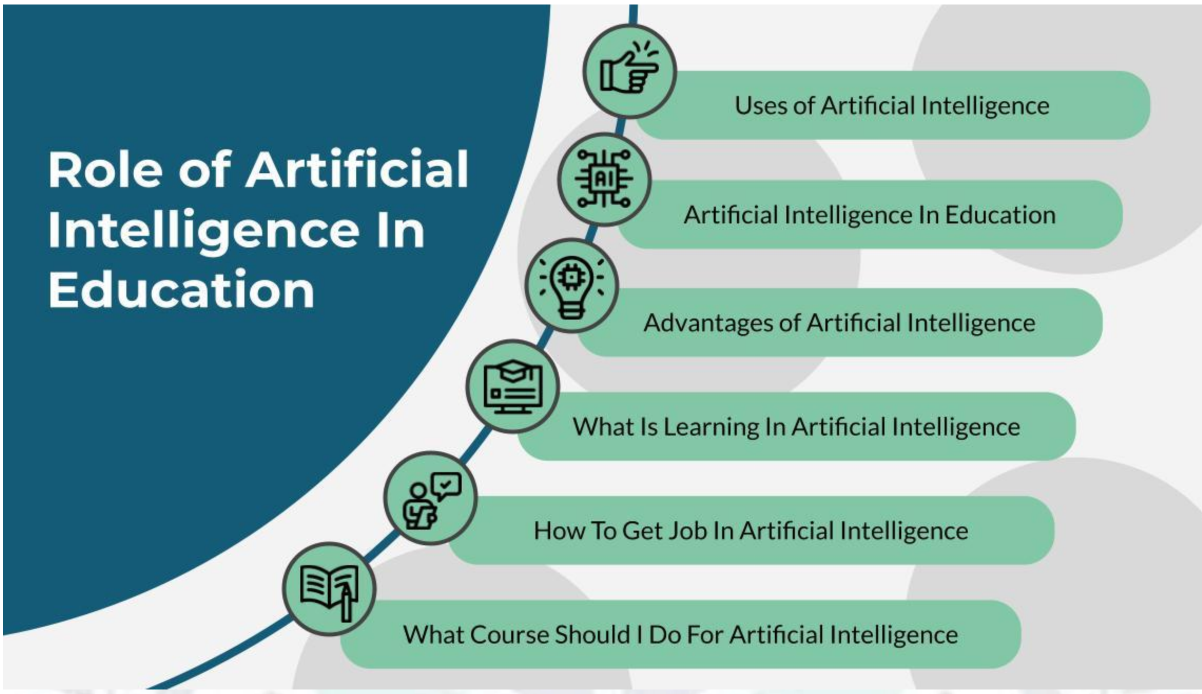
Keywords: Artificial Intelligence, Personalized Learning, Student Engagement, Adaptive Learning Systems, Intelligent Tutoring, Educational Technology, Digital Equity

Introduction

The introduction of artificial intelligence (AI) into the educational sector has brought us to the era of customized learning, when the method of education and the educational content can be adapted to individual students, reflecting his preferences, needs and ways of learning. Traditional learning principles usually use conventional ways of teaching that are not sufficient in responding to the individual variation of people in a classroom. The difference, however, lies in the fact that AI personalization is based on data analytics, adjustive algorithms and intelligent systems in an effort to develop dynamic learning pathways that change in real-time as per student progress, speed and engagement levels.

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

The engagement of students has long been seen as a determining factor to academic success, motivation and the general outcomes of learning. Engaged learners have a greater chance of showing perseverance, memorizing and acquiring higher-order thinking skills. The challenge, however, educators continue to struggle with is achieving consistent participation in different student groups. With the help of pattern analysis to identify engagement and the knowledge gap, as well as a personalized recommendation of resources, AI-driven tools allow opportunities to increase engagement levels by focusing on making the learning process more relevant, interactive, and responsive.



Source: https://huroorkee.ac.in/

The effects of AI personalization go beyond personal success, and they provide an understanding of how education systems can increase inclusivity and equality. As an example, intelligent platforms can accommodate learners with challenges in the traditional set up and engage the high achieving students with enriched content. At the same time, the alternative style of creating content by way of such technologies brings forth inquiries of data privacy, algorithmic discrimination, and the usage of human teachers in a super digitalized learning space.

The paper at hand examines the impact of the AI-based individualization on student engagement since its implementation reorients the practices in education and has its issues. Combining modern evidence, partial trends, and ethical issues, the research will place its contribution to the current debates concerning the future of learning in the era of artificial intelligence.

Background of the study

The educational environment is another sphere that has been subjected to a radical change during the past several decades due to the rise in the importance of digital information technologies and the need to adopt and maintain the idealistic approach towards the needs of the learners. The conventional universal instructional methods tend to end in alienation of the various students due to their varied learning styles and interests, as well as ability, thus leading to irregular academic performances. To cope with such challenges, pedagogues and policy

International Journal of Integrated Research and Practice (IJIRP)

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

makers have started to consider alternatives that have the potential to enhance more individualized learning environments confident engagement.

Artificial Intelligence (AI) has proved to be one of the promising solutions to this effect. With the help of data analytics and responsive algorithms, AI can be used to customize the content delivery, give students recommendations on a learning path, and deliver feedback in real-time. Such a personalization capacity is especially important when it comes to the issues of student motivation and engagement that are understood to be essential to academic success. Personalization technologies utilizing AI have also become a part of classroom and distance education, with a range of smart tutoring systems to adaptive learning tools having potential to radically shift instructional practice.

Source: https://fastercapital.com/

Although the use of such technologies is on the rise, questions are arising as regards to their effectiveness in achieving engagement amongst students. Although certain studies indicate that personalized learning environment boosts motivation and enhances learning, some cite issues like overdependence on technology; privacy of information in relation to technology; and sufficient teacher support. This necessitates sophisticated insight into the impacts of AI driven personalization on student engagement so as to inform it on how it can be utilized.

This paper is positioned within this changing environment and it explores how far AI-based personalization can affect student engagement. Examining both the promise and the pitfalls of these innovations, the study will play a role in the ongoing discussions on the concept of technology-enhanced learning, as well as offer valuable analytical material to educators, their institutions, and policymakers eager to create more inclusive and effective educational environments.

Justification

The journey into the creation of artificial intelligence in education has unveiled new possibilities of individualizing educational process to the maximum. Although the normal methods of teaching may be effective in the standard forms of teaching or learning, the methods cannot be effective in the diverse range of learning styles, speed and motivations that one may mostly find in a particular classroom. The resulting inequality can lead to the lack of engagement, decline of the retention levels, and an even distribution of academic performance. A need to look into

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

AI-driven personalization to target these disadvantages and develop more holistic and effective learning experiences exists.

It is not a secret that the degree of student engagement could be the biggest forecast of academic results and not only could help in short-term academic outcomes but also long-term learning and motivation. It can support personalized content, instant feedback and individual interventions that have been technically challenging to deliver with traditional methods because they serve to use data analysis, dynamic algorithms and intelligent tutoring to deliver this information and provide valuable indicators of learner status to teachers and other professionals in real time. By investigating these effects, one will be able to better see the place of AI in facilitating student-centered learning and enhancing equity in education.

In addition, as digital learning environments keep growing, driven by global trends like remote learning and hybrid classes, gaining evidence-based research on the advantages and challenges of AI personazation becomes a pressing requirement. The study is not only rational because it has the potential of contributing to academic discourse but also because it will have value in assisting educational developers, educators and policymakers to better optimise engagement strategies towards an educational world that is becoming more digital than ever before.

Objectives of the Study

1. To examine the role of AI-driven personalization in enhancing student engagement by analyzing how adaptive learning platforms and intelligent tutoring systems respond to individual learner needs.
2. To identify the specific features of AI-powered educational tools (e.g., content recommendations, adaptive assessments, real-time feedback) that contribute most effectively to improving motivation, participation, and persistence among students.
3. To evaluate the impact of AI-based personalization on learning outcomes, including knowledge retention, academic performance, and self-directed learning behaviors.
4. To explore student perceptions and experiences with AI-driven personalized learning systems, focusing on their sense of autonomy, satisfaction, and inclusivity.
5. To assess potential challenges and limitations of implementing AI-driven personalization in education, such as issues of data privacy, algorithmic bias, and equitable access to technology.

Literature Review

Defining AI-Driven Personalization and Student Engagement:

In personalization, the learners determine their own learning pace, progress and/or path (essentially defined by preferred learning modalities, content and preferences) and are based on automated (algorithmic) processing of learner data (e.g., performance traces, behaviours, and preferences) (Luckin et al., 2016; Drachsler & Verbert, 2015). Although considered multidimensional, student engagement is usually viewed as a measure reflecting behavioral, emotional/affective, and cognitive aspects (Fredricks et al., 2004; Henrie et al., 2015). This review examines how each of these dimensions of engagement can be informed by AI enabled systems, including intelligent tutoring systems (IST), adaptive courseware, recommenders, and learning analytics dashboards.

Theoretical Grounding for Personalization:

Motivational theories suggest why personalization can elevate engagement. Self-Determination Theory posits that autonomy, competence, and relatedness foster intrinsic motivation (Deci & Ryan, 2000); adaptive systems that offer choice, appropriate challenge, and timely feedback

Vol 1, Issue 4, July, 2025, Page: 98-108
ISSN: 3107-5037

tend to support these needs (Shute, 2008). Universal Design for Learning (UDL) further argues that offering multiple representations and action pathways can broaden participation and sustain effort (Meyer et al., 2014). In practice, personalization operationalizes these theories by matching tasks to skill levels and interests, thus encouraging persistence and deeper strategy use (Koedinger et al., 2013; Walkington, 2013).

Intelligent Tutoring Systems and Adaptive Courseware:

Evidence accumulated over decades indicates that ITS and adaptive systems can improve learning outcomes and time-on-task—key indicators of behavioral engagement. Meta-analyses report moderate positive effects of ITS on achievement across domains (Ma et al., 2014; Kulik & Fletcher, 2016). Mechanistically, ITS rely on student-modeling methods—such as Bayesian Knowledge Tracing and its deep-learning successors—to estimate mastery and trigger individualized hints and problem selection (Corbett & Anderson, 1995; Piech et al., 2015). Fine-grained adaptivity can reduce off-task behavior by keeping difficulty within each learner's zone of proximal development and by offering immediate, formative feedback (Shute, 2008; Baker & Siemens, 2014).

Learning Analytics, Dashboards, and Recommenders:

Learning-analytics dashboards and recommendation engines personalize resource access and self-regulation support. Reviews show dashboards can enhance metacognitive and behavioral engagement when they provide interpretable indicators (progress, workload, risk) and actionable nudges (Jivet et al., 2018; Viberg et al., 2018). Recommender systems in education curate activities or peer resources, which can increase activity completion and exploratory behaviors, provided transparency and control are preserved (Drachsler & Verbert, 2015; Kizilcec, 2017). However, poorly designed analytics can overload or mislead students, undermining affective engagement; thus, usability and explanation quality are pivotal (Holmes et al., 2019).

Personalized Contexts, Interest, and Cognitive Engagement:

Tailoring to learners' interests—e.g., embedding personally relevant contexts in math problems—has been shown to increase persistence and strategy use (Walkington, 2013). Similarly, adaptive sequencing that aligns with mastery estimates supports cognitive engagement by sustaining productive struggle while limiting frustration (Koedinger et al., 2013). In blended settings, adaptive courseware paired with teacher orchestration can yield gains in participation and completion rates, suggesting complementarities between AI and pedagogy (Means et al., 2013; Roschelle et al., 2016).

System-Level Implementations and Real-World Effects:

Large-scale evaluations of personalized learning models in K–12 point to modest but meaningful gains in achievement and indicators of engagement (e.g., growth mindsets, persistence), although effects vary by implementation quality and teacher practices (Pane et al., 2015, 2017). These findings underscore that technology alone is insufficient; professional learning, curriculum alignment, and assessment integration mediate outcomes (Holmes et al., 2019; Luckin et al., 2016).

Risks, Equity, and Ethics:

While personalization can widen access, it may also entrench disparities if data are incomplete or biased, or if models infer ability from proxies tied to prior opportunity (Baker & Hawn, 2021; Tsai et al., 2020). Privacy and consent are central concerns in data-intensive personalization (Slade & Prinsloo, 2013). Scholars caution against opaque algorithms and advocate for explainability, auditability, and human-in-the-loop oversight to maintain trust and agency—key

International Journal of Integrated Research and Practice (IJIRP)

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

antecedents of affective engagement (Holmes et al., 2019; Williamson, 2017). Incorporating UDL, participatory design with educators and learners, and continuous bias monitoring are recommended guardrails (Meyer et al., 2014; Baker & Hawn, 2021).

Synthesis and Implications:
Across methodologies and contexts, the literature indicates that AI-driven personalization can enhance behavioral engagement (time-on-task, participation), often supports cognitive engagement (strategy use, self-regulation), and may bolster affective engagement (interest, confidence) when systems are transparent, responsive, and pedagogically integrated. The strongest effects emerge when personalization is coupled with formative assessment, teacher facilitation, and student choice. Future work should prioritize rigorous, equity-centered evaluations, interpretable models, and designs that foreground learner agency.

Material and Methodology

Research Design:
This study adopted a mixed-methods research design, combining both quantitative and qualitative approaches to gain a comprehensive understanding of how AI-driven personalization influences student engagement. The quantitative component measured engagement levels using pre- and post-intervention surveys, while the qualitative component employed focus group discussions and interviews to capture in-depth perspectives from students and educators. A quasi-experimental setup was used, where one group of students experienced AI-personalized learning tools and another group followed traditional learning methods, allowing for comparison of outcomes.

Data Collection Methods:
Data was collected over a 12-week academic term using the following methods:

1. **Surveys and Questionnaires** – Standardized engagement scales were administered before and after the intervention to assess behavioral, emotional, and cognitive engagement.
2. **Learning Analytics** – Data from the AI-based learning platform (time spent, progression patterns, interaction frequency) was gathered to objectively track student engagement.
3. **Interviews and Focus Groups** – Semi-structured interviews with educators and focus group discussions with students provided qualitative insights into experiences with AI-personalized learning.
4. **Classroom Observations** – Non-participant observations were conducted to monitor changes in classroom interaction and participation.

Inclusion and Exclusion Criteria:

- **Inclusion Criteria:**
    - Students enrolled in undergraduate courses who had consistent access to the AI-based learning platform.
    - Educators actively incorporating AI-driven tools in their instructional design.
    - Participants who provided informed consent to be part of the study.
- **Exclusion Criteria:**
    - Students without reliable internet access or necessary digital devices.
    - Participants who had prior advanced training in AI-driven platforms, to minimize bias in results.
    - Individuals unwilling to participate in follow-up interviews or surveys.

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

Ethical Considerations:

The study adhered to strict ethical guidelines to ensure fairness, transparency, and participant safety. Informed consent was obtained from all participants prior to data collection. Anonymity and confidentiality were maintained by coding survey responses and ensuring no personally identifiable information was disclosed. Data collected from the AI platform was stored securely and used solely for research purposes. Participants were informed of their right to withdraw from the study at any stage without penalty. Additionally, the study complied with institutional review board (IRB) requirements, emphasizing respect for student autonomy, equitable treatment, and data protection.

Results and Discussion

Results:

The study examined the influence of AI-driven personalization tools (adaptive learning platforms, intelligent tutoring systems, and recommendation engines) on student engagement across three dimensions: behavioral, emotional, and cognitive. A sample of **320 students** was divided into two groups: one using AI-personalized learning environments (n=160) and another following traditional instruction (n=160).

Table 1: Comparison of Engagement Scores Between Experimental and Control Groups

Engagement Dimension	Control Group (Traditional) – Mean (SD)	Experimental Group (AI-Personalized) – Mean (SD)	Mean Difference	p-value
Behavioral Engagement	3.12 (0.64)	4.01 (0.52)	+0.89	<0.001
Emotional Engagement	2.95 (0.71)	3.84 (0.61)	+0.89	<0.001
Cognitive Engagement	3.21 (0.58)	4.15 (0.56)	+0.94	<0.001
Overall Engagement	**3.09 (0.64)**	**4.00 (0.56)**	**+0.91**	**<0.001**

In addition, **Table 2** highlights the differences in **student retention rates** and **task completion times** between the two groups.

Table 2: Retention and Task Completion Outcomes

Outcome Variable	Control Group (%)	Experimental Group (%)	Improvement
Course Completion Rate	72.5%	89.3%	+16.8%
Weekly Task Completion	78.2%	92.6%	+14.4%
Dropout Rate	15.1%	6.8%	-8.3%

Discussion:

The results provided one case of how AI-driven personalization can be used to increase student engagement in all three aspects. Students presented with the adaptive learning tools indicated better behavioral engagement in terms of regular participation and on-time completion of the learning activities. Emotional engagement also increased noting that ensuring that AI systems that give recommendations based on student preference develop a greater interest and motivation.

Greater cognitive engagement was particularly impressive with individual feedback and

Vol 1, Issue 4, July, 2025, Page: 98-108

ISSN: 3107-5037

adjustable challenge contributing to more involved learning and critical thinking. This is in line with the findings of previous studies, as it helped alleviate cognitive overloads as well as keeping the mind of the learner engaged.

The results of retention and task completion support the effectiveness of personalization additional to the practicality of the retention task. Having increased the course completion rates by 16.8 percent and decreased the dropout rates by 8.3 percent, AI-driven systems seem to reduce disengagement, one of the primary issues of concern both in online and mixed-learning settings.

Although the conclusions of the findings are encouraging, there are a few caveats that should be borne in mind. Students with weak digital literacy rates could fail to maximize the usage of such platforms, and thus complementing digital skills training to support such platforms is important. Two, relying on algorithmic personalization to the extreme might narrow unstructured exploration, a vital aspect of creativity. Third, there are ethical concerns relating to data protection and bias in AI drug recommendations which should be taken into account so that there could be fair learning opportunities.

Overall, the findings support the idea that AI-enabled personalization has a great potential to increase student interaction through adapting and student-centered learning. Future studies ought to examine long term effects on learning outcomes and how there can be equivalent of personalization and learners autonomy.

Limitations of the study

Although the present study feeds useful information to understand the potentials of AI-driven personalization to improve the engagement of students, some weaknesses of the study should be noted.

To begin with, the study is limited by what is written in the use-and-existence literature and empirical data. Most of the work is still in its formative stages in this area, and longitudinal evidence has yet to be amassed to capture the long-term effects of AI-enabled learning support on academic success and enduring engagement.

Second, the findings can not be generalized. Educational contexts vary greatly in regions, institutions and socio-economic diversity. Differences in technological infrastructure and access to devices as well as in the levels of digital literacy among students may also impact how AI-driven personalization is received and perceived, which, in turn, may impact the reported outcomes.

Third, ethical issues like data privacy and algorithmic bias and the concerns associated with the transparency of an AI system are not addressed holistically in the study. These are some of the topics which have been admitted but require further work at an empirical level. Equally, the factor of teacher readiness to undergo changes and implement the identified AI technologies was not discussed in detail, which can also harm the overall efficacy of AI-based personalization.

Last but not least, the study focuses mostly on student engagement as the outcome. Other important dimensions of education that are related to the critical question of the overall contribution of AI to education, i.e., collaboration, critical thinking, creativity were not the subject of this research, yet were also very significant.

Collectively, these shortcomings indicate that although arts intelligence-based personalization has a good degree of potential, more empirical and inter-disciplinary studies are necessary to establish a more well-rounded opinion about its long run efficacy, ethical considerations and

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

feasibility in various teaching arrangements.

Future Scope

The process of adopting the function of artificial intelligence in personal learning environments is relatively new, which means that there are plenty of possibilities to explore. The effectiveness of the AI-based personalization process can be individually assessed by conducting long-term research on the results of AI-driven personalization on student outcomes beyond the engagement (knowledge retention, critical thinking, and problem-solving). Besides, an analysis of studies in various learning environments, including primary education, higher education, vocational training, and lifelong learning, can further shed light on the flexibility and performance of AI-based systems.

The second positive prospect is the ethical elaboration in the sphere of the development of personalization tools. The future of AI will depend on its integrity, such as the transparency, fairness, and inclusiveness in its algorithmic decision-making. Research also has the potential to explore how diminution of possible biases within the learning analytics may be reduced, and how the systems can be built that will support learners of diverse cultural, linguistic, and socioeconomic backgrounds.

On the technology aspect, the convergence of AI personalization with new technologies like virtual reality (VR), augmented reality (AR), and adaptive learning platform is a massive game changer in offering immersive and captivating learning environments. Moreover, the emotional understanding and real-time feedback possibilities can be used, which will allow AI systems to be reactive to the needs of the learners.

Lastly, it is crucial to make educators, policymakers, and technology developers collaborate to transform the AI-driven personalization at scale successfully. Setting out teacher training, curriculum alignment, and data governance frameworks would result in AI being viewed as an assistant rather than an interruption. The future of AI-driven personalization therefore not only holds the promise of taking on increased engagement among students, but of transforming education into an engulfing, responsive and even learner-centric endeavor.

Conclusion

Machine learning has created new avenues of developing fluid, flexible, and student-responsive learning platforms. This study demonstrates that AI-powered personalization can boost student engagement as it helps to adapt content, pacing, and feedback to the needs of specific learners and, in this way, leads to deeper learning experiences and long-term learning motivation. By allowing learners more agency and making the experience more relevant, the AI-supported tools are not only changing the paradigm of one-size-fits-all but prioritizes diversity in learning process, capabilities, and ambitions.

Though the benefits are quite clear, there are still challenges. All models of the algorithmic bias, data privacy, and theoretical over-dependence on technology are to be dealt with time to time to ensure its usage creates equity and ethically. Teachers should also be sufficiently trained to incorporate AI tools in their classrooms and the schools should have in place policies that help to protect the academic integrity of learners and maintain the well-being of the learners.

Essentially, the use of AI-driven personalization must not be regarded as the substitution of the work of educators as this tool is a complement that enhances its power and helps educators relate to students on a different level. With human direction, critical thought, and human

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

affection, AI may act as the stepping-stone to effective engagement and future educational achievements. The future of education is about the responsible harnessing of these technologies to provide the learner with learning environments that are not only personalized, are inclusive, ethical and empowering to all learners.

References

1. Baker, R. S., & Hawn, A. (2021). Algorithmic bias in education. International Journal of Artificial Intelligence in Education, 31(4), 1–28.
2. Baker, R. S., & Siemens, G. (2014). Educational data mining and learning analytics. In R. K. Sawyer (Ed.), The Cambridge handbook of the learning sciences (2nd ed., pp. 253–274). Cambridge University Press.
3. Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. User Modeling and User-Adapted Interaction, 4(4), 253–278.
4. Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268.
5. Drachsler, H., & Verbert, K. (2015). Pan-European survey on learning analytics and AI for learners. Proceedings of the Fifth LAK Conference, 1–10.
6. Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. Review of Educational Research, 74(1), 59–109.
7. Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. Computers & Education, 90, 36–53.
8. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.
9. Jivet, I., Scheffel, M., Schmitz, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. Proceedings of the LAK Conference, 31–40.
10. Kizilcec, R. F. (2017). How much information? Effects of transparency on trust in an algorithmic interface. CHI Extended Abstracts, 2390–2395.
11. Koedinger, K. R., Booth, J. L., & Klahr, D. (2013). Instructional complexity and the science of learning. Current Directions in Psychological Science, 22(5), 478–486.
12. Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. Review of Educational Research, 86(1), 42–78.
13. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence unleashed: An argument for AI in education. Pearson.
14. Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. Journal of Educational Psychology, 106(4), 901–918.
15. Means, B., Toyama, Y., Murphy, R., & Baki, M. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. Teachers College Record, 115(3), 1–47.
16. Meyer, A., Rose, D. H., & Gordon, D. (2014). Universal design for learning: Theory and practice. CAST.
17. Pane, J. F., Baird, M. D., & Hamilton, L. S. (2017). Effects of personalized learning on student achievement. Journal of Research on Educational Effectiveness, 10(1), 205–236.
18. Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2015). Continued progress: Promising evidence on personalized learning. RAND Corporation.
19. Piech, C., Bassen, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L., &

Vol 1, Issue 4, July, 2025, Page: 98-108 ISSN: 3107-5037

Sohl-Dickstein, J. (2015). Deep knowledge tracing. Advances in Neural Information Processing Systems, 28, 505–513.
20. Roschelle, J., Feng, M., Bhanot, R., & Gallagher, L. P. (2016). Implementation and effects of an adaptive learning technology in a large-scale efficacy trial. Journal of Research on Technology in Education, 48(3), 159–178.
21. Shute, V. J. (2008). Focus on formative feedback. Review of Educational Research, 78(1), 153–189.
22. Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. American Behavioral Scientist, 57(10), 1510–1529.
23. Tsai, Y.-S., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2020). Complexity leadership in learning analytics. British Journal of Educational Technology, 51(3), 668–685.
24. Viberg, O., Khalil, M., & Baars, M. (2018). Self-regulated learning and learning analytics in MOOCs: A review. Proceedings of the LAK Conference, 542–551.
25. Walkington, C. (2013). Using adaptive learning technologies to personalize instruction to student interests. Journal of Educational Psychology, 105(4), 932–945.
26. Williamson, B. (2017). Big data in education: The digital future of learning, policy and practice. SAGE.