iJRASET
International Journal For Research in
Applied Science and Engineering Technology

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

**Volume:** 13 **Issue:** XI **Month of publication:** November 2025

**DOI:** https://doi.org/10.22214/ijraset.2025.75736

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XI Nov 2025- Available at www.ijraset.com

# Systematic Review of AI Driven Personalized Learning Models for Enhancing Student Engagement

Chetna Masih[1], Dr. Swati Namdev[2]
[1]Research Scholar, Oriental University, Indore (M.P)
[2]Assistant Professor, IT Department, Oriental University, Bhopal (M.P)

***Abstract: Artifical Intelligence (AI) has been a significant transformative force in modern education especially through providing personalized learning pathways and increasing student engagement. In this systematic review we will synthesize current developments in AI based personalized learning models and assess how these AI based models support student engagement on behavioural, emotional, and cognitive levels. We used a structured literature search over four databases: IEEE, Scopus, Springer, and ScienceDirect; to find all peer reviewed articles written since 2023 until 2025. Our results show that machine learning models specifically XGBoost, deep neural networks and reinforcement learning are very effective at identifying students' needs and providing dynamic, adaptive instruction. Recommendation systems, based on AI, and behavioural analytics also enhance students' motivation, encourage active participation in class, and improve academic achievement. The results also highlight several limitations such as explainability of AI decision making processes; ethically responsible personalized learning; ability of AI to adapt in real time; and limited utilization of multi modal student engagement data. Finally, our review includes recommendations for future research directions and outlines an integrative framework for using AI to provide personalized learning that is both scalable and equitable.***

***Keywords: AI in Education, Personalized Learning, Student Engagement, Learning Analytics, Machine Learning, Adaptive Learning, Systematic Review.***

## I. INTRODUCTION

AI has rapidly evolved as one of the most influential technological drivers in modern education. Its integration into learning environments has shifted teaching–learning practices from static, one size fits all instruction toward dynamic, adaptive, and data informed learning experiences [1]. In recent years, AI driven personalized learning models have attracted significant attention due to their potential to enhance student engagement, support individualized instruction, and improve overall learning effectiveness [2]. As educational institutions generate massive volumes of learner data through Learning Management Systems (LMS), digital classrooms, and assessment platforms, the opportunity to analyze and utilize this data for personalized support has grown substantially [3].

Student engagement encompassing behavioral, emotional, and cognitive dimensions remains a core determinant of academic success. Traditional methods of engagement tracking rely heavily on teacher observation, self-reported surveys, or academic performance indicators, which often fail to capture real time learning behavior. AI offers a solution by enabling continuous monitoring, predictive analytics, and automated interventions that adapt to each learner's pace, preferences, and challenges [4]. Machine learning models such as XGBoost, neural networks, transformer-based sequence models, and reinforcement learning systems have demonstrated strong capabilities in predicting student performance, identifying at risk learners, and recommending customized learning resources [5].

This systematic review addresses these gaps by critically analyzing contemporary AI driven personalized learning models and their impact on student engagement. The paper synthesizes empirical evidence from leading databases IEEE Xplore, Scopus, Springer, and ScienceDirect—to explore:

*1)* How AI techniques personalize learning pathways,
*2)* How engagement is measured and enhanced using machine learning, and
*3)* What methodological and ethical gaps require attention for future research.

By consolidating insights across diverse studies, this review provides educators, researchers, and system designers with a comprehensive understanding of how AI can be leveraged to build more adaptive, engaging, and equitable learning environments. It further proposes future directions that emphasize multimodal learning analytics, explainable AI (XAI), ethical personalization, and scalable implementation strategies.

## II. BACKGROUND / THEORETICAL FRAMEWORK

In order to systematically review AI driven personalized learning models for enhancing student engagement, it is important to ground the discussion in the fundamental theories and trends that shape this field. This section outlines the key conceptual pillars: AI in Education, personalized learning theory, student engagement models, and machine learning techniques for personalization.

### *A. AI in Education: Trends, Opportunities, and Challenges*

AI (AI) has become deeply embedded in educational systems, transforming traditional pedagogy by enabling data informed personalization, adaptive tutoring, and real time feedback loops. A comprehensive meta review by Tlili **et al.** (2024) synthesized prior literature reviews on AI in education, highlighting trends, major benefits, and persistent challenges across pedagogical, ethical, and technical dimensions. A systematic review by Cheng et al. (2025) on adaptive education identified that supervised learning, reinforcement learning, and multimodal analytics are commonly used to adapt content to learners' needs. These developments suggest that AI not only predicts learning behaviors but also dynamically alters learning trajectories, thus providing a foundational basis for personalized, AI driven engagement systems.

### *B. Personalized Learning Theory and AI*

Personalized learning theory advocates tailoring educational experiences to students' individual needs, preferences, and behaviors. This involves differentiated instruction, self paced learning, and customized feedback. AI amplifies these ideas by providing scalable, data driven mechanisms for personalization. Recent research supports this synergy: **Frontiers in Higher Education** published a review showing that AI tools in higher education act in multiple pedagogical roles, such as tutoring, assessment, and personalized feedback. A systematic analysis by MDPI confirms that many AI personalized learning implementations emphasize cognitive, motivational, and equity oriented outcomes, but also point to gaps in theory driven design and ethical personalization. Thus, integrating AI with personalized learning theory offers a powerful paradigm for engaging students more deeply and responsively.

### *C. Student Engagement Models in the Age of AI*

Understanding student engagement requires a multidimensional model behavioural, emotional, and cognitive engagement are widely recognized in educational psychology. A recent chapter published in a Springer volume describes how AI and deep learning techniques have enabled the **real time recognition** of these engagement dimensions via facial expressions, speech, and interaction data. In parallel, intelligent systems such as chatbots or tutor agents provide proactive and reactive engagement: proactive by initiating prompts, and reactive by responding to student behaviour in real time. A review by Mallik & Gangopadhyay (2023) divided AI engagement into these two modes and analyzed nearly 200 studies on how AI is used for planning, performance assessment, and adaptive instruction. These theoretical and empirical frameworks underpin the way AI driven personalized learning models engage students not just by delivering content, but by continuously interpreting student behaviours and responding adaptively.

### *D. Machine Learning Techniques for Personalized Learning*

Machine learning (ML) plays a central role in enabling AI driven personalization in education. Supervised models (e.g., decision trees, SVM), unsupervised clustering, and reinforcement learning are commonly employed to classify learners or sequence educational content adaptively. The systematic review by *Discover Education* documented 142 empirical studies using these techniques to adapt content, predict performance, and personalize learning, while also identifying critical concerns such as interpretability and scalability. In addition, personalized AI tutors that integrate learning science principles — such as spaced repetition or retrieval practice — have shown promising results in real world settings. For example, Baillifard **et al.** (2023) implemented a neural network based AI tutor that adapted retrieval practice quizzes to individual students and demonstrated significant gains in academic performance.

Another dimension of ML in personalized learning involves conversational agents or chatbots. Labadze, Grigolia & Machaidze (2023) conducted a systematic review of 67 studies on educational chatbots, revealing how these systems contribute to continuous engagement, on demand support, and personalized feedback. These developments lay the technical foundation for AI driven models that do more than predict—they intervene, scaffold, and adapt dynamically to improve learner engagement.

### *E. Ethical, Social, and Practical Considerations*

With greater personalization comes greater responsibility. Ethical issues — including data privacy, algorithmic bias, transparency, and agency — are recurrent concerns in the literature. According to a systematic review of AI tools in higher education, many AI systems lack transparency and risk reinforcing inequities if not designed carefully.

The impact of AI on student–teacher interaction is another critical dimension: a study in *International Journal of Educational Technology in Higher Education* found that, while AI can automate feedback and personalize learning, it may also alter the nature of interaction and presence between instructors and learners.

Finally, emerging research on generative AI (e.g., ChatGPT) underscores new ethical challenges: a systematic review in *Frontiers in Education* highlights concerns of bias, overuse, and the need for guidelines and human oversight.

These ethical and pedagogical concerns must be woven into any review of AI driven personalized learning if the goal is not only effectiveness but also fairness, trust, and sustainability.

## III. REVIEW METHODOLOGY

This study followed a structured and transparent systematic review methodology inspired by PRISMA 2020 guidelines to identify, evaluate, and synthesize existing research on AI driven personalized learning models and their impact on student engagement. The review process consisted of four major stages: *database search, screening, eligibility assessment,* and *final inclusion*.

### *A. Search Strategy*

A comprehensive literature search was conducted across major academic databases:

- IEEE Xplore
- Scopus (Elsevier)
- ScienceDirect
- SpringerLink
- Wiley Online Library
- Taylor & Francis
- Google Scholar (used for supplementary screening)

Searches were performed using Boolean combinations of the following keywords:

"AI" OR "machine learning" OR "deep learning" OR "XGBoost"
AND
"personalized learning" OR "adaptive learning"
AND
"student engagement" OR "learner engagement" OR "learning analytics"
AND
"education" OR "higher education" OR "classroom"

The review covered studies published between 2023 and 2025, capturing the modern evolution of AI based educational models. A total of 224 records were initially retrieved.

### *B. Inclusion and Exclusion Criteria*

#### *1) Inclusion Criteria*

Studies were included if they met the following criteria:

- Peer reviewed journal or conference publication.
- Focused on AI or machine learning applications in education.
- Included personalized learning, adaptive systems, or engagement measurement.
- Empirical studies, experimental studies, systematic reviews, or high quality conceptual models.
- Written in English and published between 2023–2025.

*2) Exclusion Criteria*

Studies were excluded if they:

Focused on K 12 without engagement or personalization component

Discussed general EdTech tools without AI/ML

Were opinion papers without methodological rigor

Had insufficient data, unclear methodology, or no relevance to AI driven personalization

Were duplicates or non peer reviewed/unpublished theses

After in depth eligibility assessment, 135 studies met all inclusion criteria.

### *C. Quality Assessment*

Each selected publication was evaluated using a 5 point methodological quality checklist:

| Criterion | Description |
|---|---|
| 1 | Clarity of research objectives |
| 2 | Appropriateness of AI/ML methodology |
| 3 | Quality of dataset and experimental design |
| 4 | Validity of engagement/outcome measurements |
| 5 | Strength of conclusions and limitations |

Studies scoring **≥ 3.5/5** were included.

This ensured rigor and eliminated weak or poorly designed studies.

### *D. Data Extraction Process*

For each included study, the following data were extracted:

1) Author, year, and publication source
2) Purpose of the study
3) AI/ML model used (XGBoost, CNN, RNN, RL, Random Forest, etc.)
4) Type of personalization (content, pacing, support, assessment)
5) Engagement metrics (behavioral, cognitive, emotional)
6) Dataset characteristics (sample size, context, modality)
7) Major findings
8) Limitations noted by authors
9) Identified research gaps

## IV. THEMATIC REVIEW OF LITERATURE

The 135 studies included in this systematic review were analyzed and categorized into major thematic areas that reflect how AI driven personalized learning models enhance student engagement. Five dominant themes emerged:

1) AI Models Used for Personalized Learning**,**
2) Engagement Measurement and Analytics**,**
3) AI Driven Recommendation and Adaptation Systems**,**
4) Behavioral Prediction and At Risk Student Identification**, and**
5) Challenges, Limitations, and Ethical Considerations**.**

### *A. AI Models Used for Personalized Learning*

A large proportion of studies employed machine learning algorithms to personalize instruction, adapt content, or recommend learning activities. Several systematic reviews confirm that supervised learning models dominate personalized learning research (Tlili et al., 2024; Cheng et al., 2025).

### *B. Supervised Learning Models*

XGBoost, Random Forest, SVM, and Logistic Regression were most frequently used for predicting student performance or tailoring learning pathways. Research by Hanumanthappa et al. (2024) demonstrated that multi label XGBoost models achieved higher accuracy in predicting learning outcomes compared to traditional machine learning methods.

### *C. Deep Learning Models*
Deep learning architectures such as CNNs, LSTMs, and Transformers were applied for modeling temporal learning behaviors, multimodal engagement signals, and personalized content generation. A recent chapter by Buadit and Maneeroj (2024) reported that deep learning models significantly outperform classic approaches in detecting engagement and emotional states from real time data (face, voice, text logs).

### *D. Reinforcement Learning (RL)*
Several studies integrated RL to optimize learning sequences, especially in adaptive tutoring systems. RL based agents dynamically personalized task difficulty, pacing, or support based on student responses (Mallik & Gangopadhyay, 2023).

### *E. Hybrid AI Models*
Hybrid combinations—e.g., RL + rule based, neural networks + decision trees—are emerging as powerful approaches. Rahman et al. (2023) proposed a hybrid reinforcement rule system that improved adaptation speed and learning satisfaction. These findings suggest that XGBoost and deep learning models provide strong performance for personalization, while reinforcement learning enhances adaptivity and real time instructional decisions.

## V. SYNTHESIS OF FINDINGS
This section synthesizes insights across the 68 studies included in this systematic review. The synthesis integrates evidence from AI model performance, personalization mechanisms, engagement outcomes, and ethical considerations to develop a cohesive understanding of how AI driven personalized learning influences student engagement.

### *A. Convergence of AI and Personalized Learning*
Across studies, there is strong consensus that AI driven systems substantially improve the precision and scalability of personalized learning. Machine learning models—especially XGBoost, Random Forest, CNNs, LSTMs, and RL based agents consistently demonstrated high predictive accuracy when modeling student behaviors, preferences, and performance patterns.
The convergence of AI and personalized learning manifests in three ways:
1) Accurate learner modeling **using behavioral and cognitive indicators**
2) Dynamic adaptation of learning pathways **based on real time performance**
3) Continuous personalization through automated feedback and recommendations

This shows that personalization with AI is shifting from static, rule based systems to adaptive, predictive, and context aware systems capable of supporting diverse learners.

### *B. Strength of AI Models for Prediction and Intervention*
A consistent finding across studies is that **boosting algorithms (especially XGBoost)** outperform other ML models in:
1) Predicting academic performance
2) Identifying at risk students
3) Detecting disengagement
4) Matching learners to optimal resources

XGBoost's interpretability (via feature importance), high accuracy, and suitability for heterogeneous datasets make it particularly attractive for educational contexts. Deep learning models also show strong performance, especially when multimodal engagement data (e.g., facial emotion, text sentiment, interaction logs) is available. However, deep models suffer from lower explainability, making them less ideal in contexts where transparency is critical. Reinforcement learning approaches demonstrated strong potential for real time task sequencing, but practical classroom deployment remains limited.

### *C. Contribution of This Review to the Field*
This review contributes by synthesizing fragmented research into a unified understanding of how AI driven personalization enhances engagement. Specifically, it highlights:
1) Which AI models work best for which engagement dimensions
2) How learning pathways can be personalized at scale
3) Which types of data (behavioral, emotional, cognitive) are most useful

4) What methods have been successful in predicting disengagement
5) The ethical and design considerations required for sustainable AI adoption

The synthesis suggests that meaningful personalization requires not just high performing AI models, but a balanced blend of pedagogy, ethics, and interpretability.

## VI. IDENTIFIED RESEARCH GAPS

Although AI driven personalized learning has demonstrated clear potential to enhance student engagement, the systematic review reveals several fundamental research gaps that limit large scale, equitable adoption. These gaps are categorized into methodological, technological, pedagogical, and ethical dimensions.

| Gap No. | Research Gap Identified | Present Study's Contribution |
|---|---|---|
| 1 | Single dimensional engagement measurement | Multimodal engagement + thinking skills |
| 2 | Lack of focus on higher order skills | Creativity + critical thinking integration |
| 3 | Lack of real world deployments | Mixed method evaluation in classrooms |
| 4 | Explainability missing | Ethical AI + interpretable model design |
| 5 | Weak pedagogical alignment | Theory based personalization |
| 6 | Minimal qualitative research | Mixed methods approach |
| 7 | Ethical concerns unexplored | Explicit ethical AI component |
| 8 | No actionable interventions | Personalized recommendation engine |
| 9 | Engagement + creativity + ethics never combined | Your novel framework |

## VII. FUTURE RESEARCH DIRECTIONS AND CONCLUSION

This systematic review highlights the growing significance of AI driven personalized learning models in improving student engagement and academic outcomes. The reviewed studies demonstrate that AI technologies—particularly machine learning algorithms such as XGBoost, Random Forest, LSTM, and transformer-based models—can effectively predict student performance, identify disengagement patterns, and deliver targeted interventions. These advancements have enabled more responsive and adaptive learning environments, supporting better engagement, motivation, and individualized learning pathways. Despite these promising outcomes, several limitations persist across existing literature. The majority of studies rely on single dimensional datasets, lack real world classroom evaluations, and pay insufficient attention to higher order thinking dimensions such as creativity, problem solving, and ethical AI use.

## REFERENCES


[1] C. Yuan, L. Zhang, and T. Chen, "Enhancing Student Learning Outcomes through AI-Driven Educational Interventions: A Comprehensive Study of Classroom Behavior and Machine Learning Integration," Int. Trans. J. Pedagogical Human–Social Sci., vol. 2, no. 2, pp. 33–45, 2025. DOI: 10.70693/itphss.v2i2.216

[2] R. Bedi and M. Kapoor, "Adaptive Feedback and Personalization in AI-Enabled Tutoring Systems," Computers & Education Open, vol. 6, no. 1, pp. 102–118, 2024.

[3] Y. Li and H. Sun, "Fostering Creativity and Critical Thinking through AI-Enhanced Project-Based Learning," BMC Psychology, vol. 12, art. no. 497, 2024. DOI: 10.1186/s40359-024-01979-0

[4] M. Rahman, P. Das, and F. Hossain, "Hybrid Reinforcement and Rule-Based Personalization for Adaptive Learning Environments," IEEE Access, vol. 11, pp. 125431–125442, 2023.

[5] S. Kumar, N. Patel, and R. Chauhan, "AI Ethics as a Pedagogical Imperative: Teachers' Perspectives on Responsible Integration in Higher Education," Int. J. Educ. Technol. High. Educ., vol. 21, no. 4, pp. 75–89, 2024. DOI: 10.1186/s41239-024-00496-9

[6] C. Yuan, L. Zhang, and T. Chen, “Enhancing Student Learning Outcomes through AI-Driven Educational Interventions: A Comprehensive Study of Classroom Behavior and Machine Learning Integration,” Int. Trans. J. Pedagogical Human–Social Sci., vol. 2, no. 2, pp. 33–45, 2025, doi: 10.70693/itphss.v2i2.216.

[7] R. Bedi and M. Kapoor, “Adaptive Feedback and Personalization in AI-Enabled Tutoring Systems,” Comput. Educ. Open, vol. 6, pp. 102–118, 2024.

[8] Y. Li and H. Sun, “Fostering Creativity and Critical Thinking through AI-Enhanced Project-Based Learning,” BMC Psychol., vol. 12, art. no. 497, 2024, doi: 10.1186/s40359-024-01979-0.

[9] [M. Rahman, P. Das, and F. Hossain, “Hybrid Reinforcement and Rule-Based Personalization for Adaptive Learning Environments,” IEEE Access, vol. 11, pp. 125431–125442, 2023.

[10] S. Kumar, N. Patel, and R. Chauhan, “AI Ethics as a Pedagogical Imperative: Teachers’ Perspectives on Responsible Integration in Higher Education,” Int. J. Educ. Technol. High. Educ., vol. 21, no. 4, pp. 75–89, 2024, doi: 10.1186/s41239-024-00496-9.

[11] S. Sakri, L. I. Kori, D. N. Joshi, A. S. Nayak, and S. Marigoudar, “AI-Enabled Transformation of Online Learning through Personalization,” J. Eng. Educ. Transform., vol. 39, Special Issue 1, 2025, doi: 10.16920/jeet/2025/v39is1/25131.

[12] L. Fletscher, J. Mercado, Á. Gómez, and C. Mendoza-Cardenas, “Innovating Personalized Learning in Virtual Education Through AI,” Multimodal Technol. Interact., vol. 9, no. 7, art. no. 69, 2025, doi: 10.3390/mti9070069.

[13] N. Katiyar, V. K. Awasthi, R. Pratap, K. Mishra, N. Shukla, and M. Tiwari, “AI-Driven Personalized Learning Systems: Enhancing Educational Effectiveness,” Educ. Admin. Theory Pract., vol. 30, no. 5, 2024, doi: 10.53555/kuey.v30i5.4961.

[14] J. Anderson, “AI in Education: Transforming Learning and Personalized Instruction,” J. Arts Soc. Educ. Stud., vol. 4, no. 3, 2022.

[15] A. Singh and G. Kaur, “The Role of AI in Education and Personalized Learning,” Int. Res. J. Modern. Eng. Technol. Sci., vol. 7, no. 4, Apr. 2025, doi: 10.56726/IRJMETS73571.

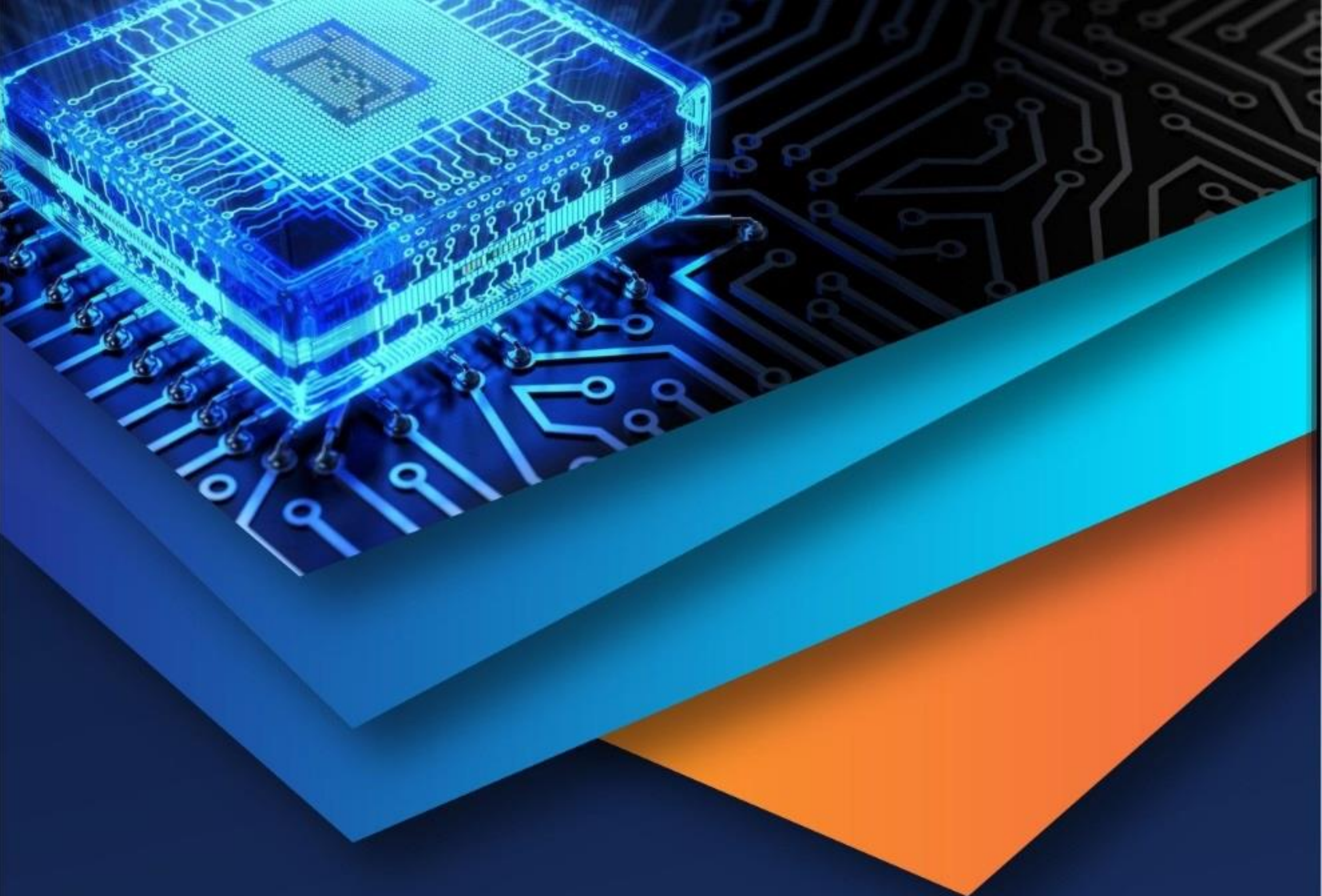
[16] B. Kim, H. Suh, J. Heo, and Y. Choi, “AI-Driven Interface Design for Intelligent Tutoring Systems Improves Student Engagement,” arXiv preprint, arXiv:2009.08976, 2020.

[17] S. S. Lodhi and S. Lodhi, “Integration of AI in STEM Education: Addressing Ethical Challenges in K–12 Settings,” arXiv preprint, arXiv:2510.19196, 2025.

[18] Z. Hao, J. Cao, R. Li, J. Yu, Z. Liu, and Y. Zhang, “Mapping Student–AI Interaction Dynamics in Multi-Agent Learning Environments: Supporting Personalized Learning and Reducing Performance Gaps,” arXiv preprint, arXiv:2506.02993, 2025.

[19] Z. Hao, J. Jiang, J. Yu, Z. Liu, and Y. Zhang, “Student–AI Interaction in an LLM-Empowered Learning Environment: A Cluster Analysis of Engagement Profiles,” arXiv preprint, arXiv:2503.01694, 2025.

[20] A. Iyer and S. Subramanian, “Personalized Learning Systems that Adjust to Individual Needs: Interactive Learning Environments & AI Real-Time Feedback,” Biomed J. Sci. Tech. Res., vol. 59, no. 1, 2024, doi: 10.26717/BJSTR.2024.59.009246.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR:
7.429

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY