International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

AI-based personalised learning system

Khushpreet Kaur, Anrika, Kashish, Ekta, Dr. Rajat Takkar
Chitkara University Institute of Engineering and Technology,
Chitkara University, Punjab,140401, India

Abstract- — The inability of existing online learning platforms to adapt to individual learner needs remains a fundamental and unresolved challenge in educational technology, contributing to persistently high dropout rates and poor knowledge retention across self-paced digital learning environments. This research proposes and evaluates a conversational AI assessment framework combined with dynamic personalised learning plan generation as a viable solution to this challenge. The study investigates whether natural, dialogue-based learner profiling yields more meaningful personalisation than conventional form-based or performance-data-driven approaches, and whether adaptive, quiz-based feedback integrated with multimodal resource matching improves learner engagement compared to uniform content delivery. A prototype platform named Flint was developed to implement and evaluate these research propositions, employing a dual-AI-engine architecture that addresses reliability and hallucination concerns identified in prior literature. Results demonstrate that conversational profiling successfully captures richer individual learner profiles, that dynamically generated plans align more closely with individual needs than static curricula, and that integrated gamification sustains motivation across extended learning engagements. The findings provide practical evidence to the growing body of research on AI-driven personalised education and demonstrate the feasibility of deploying large language model-powered individualised learning experiences at scale.

Keywords: Personalised Learning, Artificial Intelligence, Conversational Assessment, Large Language Models, Adaptive Learning, E-Learning, Intelligent Tutoring Systems.

I. INTRODUCTION

Artificial intelligence-based personalised learning systems are becoming increasingly prominent in modern education, driven by the growing recognition that traditional one-size-fits-all instructional approaches are fundamentally inadequate for diverse learner populations. The global e-learning market has witnessed unprecedented expansion over the past decade, with millions of learners worldwide enrolling in online courses across platforms such as Coursera, Udemy, and Khan Academy. Yet despite this remarkable growth, a persistent and well-documented challenge remains — the inability of existing systems to adapt meaningfully to individual learner needs, preferences, and goals. Studies consistently report that Massive Open Online Course completion rates remain between 5 and 15 per cent, a figure that has shown little meaningful improvement despite enormous investment in platform development and content quality. This chronic failure is not a content problem — it is a personalisation problem.

The root cause of this failure lies in how existing platforms treat learners. A complete beginner and an experienced practitioner enrolling in the same course receive identical content, in the same sequence, delivered through the same video lecture format, at the same pace. There is no assessment of what the learner already knows, no understanding of how they best absorb information, and no accommodation for the time they realistically have available each day. The result is frustration, disengagement, and ultimately abandonment outcomes that are entirely predictable when instruction is disconnected from the individual it is meant to serve.

Recent advances in generative artificial intelligence and large language models have opened genuinely new possibilities for addressing this gap. Generative AI systems are now capable of engaging learners in natural language dialogue, understanding context and intent, and producing entirely customised educational content tailored to specific individual profiles. Research has demonstrated that AI-powered personalised learning systems can significantly improve educational outcomes compared to conventional platforms, and that large language models can serve as effective intelligent tutoring agents capable of providing contextually relevant, adaptive instructional support. Simultaneously, the emergence of AI-driven adaptive learning platforms has shown that real-time personalisation, adjusting content, pacing, and feedback based on demonstrated learner performance, produces measurably better engagement and retention than static content delivery.

However, significant gaps remain in the current research landscape. Most existing adaptive systems rely on implicit performance signals rather than explicit conversational profiling, meaning they infer learner preferences from observed behaviour rather than understanding them directly. Few platforms integrate multimodal resource matching that accommodates diverse learning method preferences across video, reading, practice, and project-based modalities. And while AI hallucination in learning systems has been identified as a critical reliability concern that must be addressed before AI-driven platforms can be deployed responsibly, few systems have implemented robust fallback mechanisms that guarantee consistent quality regardless of AI engine availability.

This paper presents Flint, a novel AI-powered personalised learning platform designed to address these gaps comprehensively. Flint introduces the Know Me, Teach Me conversational assessment framework, in which an AI learning coach named Spark engages each learner in structured natural dialogue to understand their learning goal, current knowledge level, preferred learning style, favoured study methods, and daily time availability — building a complete learner profile before any content is generated. Based on this profile, Flint's dual AI engine — combining Claude AI as the primary generative engine with an intelligent rule-based fallback that mitigates hallucination risks — dynamically generates a personalised week-by-week learning roadmap populated with resources matched across six distinct modalities. An adaptive quiz system evaluates comprehension after every topic and adjusts the learning trajectory based on demonstrated performance. A gamification layer featuring experience points, levels, and streaks provides the motivational scaffolding that sustains engagement across the full duration of the learning journey, supported by substantial evidence that gamified learning environments produce measurable improvements in student motivation and academic outcomes.

The contributions of this work are fourfold. First, the design and implementation of a seven-stage conversational AI assessment framework for deep learner profiling through natural dialogue. Second, a dual AI engine architecture that combines the personalisation quality of large language models with the reliability of a rule-based fallback system. Third, a multi-modal resource matching system spanning six distinct learning modalities. Fourth, a comprehensive comparative evaluation demonstrating Flint's superiority over five leading online learning platforms across twelve feature dimensions.

II. LITERATURE REVIEW

Various researchers have examined AI-based personalised learning systems and their impact on education. The key observations from these studies are outlined below.

A. AI-based personalised learning system

Artificial intelligence-based personalised learning has emerged as one of the most actively researched areas in educational technology over the past several years. The fundamental premise — that AI can analyse individual learner characteristics and deliver tailored instructional experiences at scale — has moved from theoretical proposition to practical implementation across a growing number of systems and platforms. A comprehensive systematic review of AI personalised learning trends concluded that the field is rapidly maturing, and that conversational AI and generative models represent the most promising frontier for next-generation personalised education. Their review identifies the absence of pre-learning profiling as the most significant unaddressed gap in current implementations, a gap that Flint directly targets through its Know Me, Teach Me assessment framework.

Research examining AI-driven personalised learning path generation across lifelong learning contexts, finding that systems capable of generating dynamic, individualised learning paths significantly outperform static curriculum delivery in both learner satisfaction and knowledge retention. Their work establishes that the quality of a personalised learning path is directly determined by the depth and accuracy of the learner profile on which it is based — reinforcing Flint's design decision to invest heavily in conversational profiling before any plan generation occurs. An empirical further demonstrated in an empirical study that AI-driven personalised learning systems operating in data-driven environments produce measurably superior educational outcomes compared to conventional platforms, with significant improvements in learner engagement, task completion, and assessed knowledge acquisition.

Collectively, these studies establish a clear and consistent research consensus: personalisation works, AI can deliver it at scale, and the quality of the learner profile is the most critical determinant of personalised effectiveness. Flint builds directly on this consensus, implementing a seven-stage conversational profiling system that collects richer and more accurate learner profile data than any form-based or performance-data-driven alternative.

B. Generative AI and Large Language Models in Education

The emergence of large language models has fundamentally expanded what is possible in AI-driven education. A thorough analysis of the opportunities and challenges presented by large language models in educational contexts, demonstrating that LLMs possess genuine capability to personalise instructional dialogue, explain concepts at varying levels of complexity, generate assessment questions, and provide formative feedback — all of which are core functions of Flint's Spark AI engine [9]. Their work also identified the importance of thoughtful prompt engineering and system design in harnessing LLM capabilities responsibly, a finding that directly informed Flint's three-prompt architecture for assessment conversation, plan generation, and quiz creation.

A systematic review of LLM applications in education published in 2025 examined empirical evidence across multiple deployment contexts, finding consistent positive effects on learner engagement, personalisation quality, and instructional responsiveness compared to traditional e-learning approaches. The review specifically highlights conversational tutoring and automated feedback generation as the two application areas where LLMs demonstrate the strongest and most consistent performance advantages — precisely the two functions that Claude AI performs in Flint's dual engine architecture.

Research investigating the generation of in-context personalised feedback through large language models in intelligent tutoring systems, demonstrating that LLM-generated explanations and feedback are perceived by learners as significantly more helpful, relevant, and motivating than generic pre-written feedback [10]. This finding directly supports Flint's decision to use Claude AI for quiz question generation and explanation, where contextually tailored explanations after each question provide genuine educational value beyond simple answer revelation. A particularly relevant precedent is an LLM-based personalised tutoring system using retrieval-augmented generation and prompt engineering that demonstrates the practical viability of deploying LLM-powered tutoring at scale with acceptable reliability and personalisation quality.

C. Intelligent Tutoring and Adaptive Learning Systems

Intelligent tutoring systems represent a well-established research tradition that predates the LLM era, providing important foundational insights for Flint's design. A real-time adaptive learning model that leverages AI to personalise education dynamically, demonstrating that systems capable of adjusting instructional content and pacing in response to real-time learner signals produce significantly higher engagement and learning efficiency than static alternatives. Their model shares important architectural similarities with Flint, particularly in the emphasis on real-time adaptation and individualised experience delivery, though Flint extends this approach through conversational profiling and multi-modal resource matching that their system does not implement.

Investigation of deep reinforcement learning to personalised AI tutoring in intelligent education systems and adaptive e-learning platforms, reporting a 28 per cent improvement in learning efficiency and a 35 per cent improvement in engagement rates compared to traditional adaptive learning systems. While Flint employs large language models rather than deep reinforcement learning as its primary AI mechanism, the performance gains validate the broader research hypothesis that AI-driven adaptive tutoring produces meaningfully superior outcomes to conventional approaches. A decentralised autonomous AI agent architecture for real-time adaptive personalised learning that represents one of the closest existing system designs to Flint, demonstrating the viability of autonomous AI agents as the primary driver of learning personalization.

A multiple assistant AI chatbot ecosystem for personalised exam preparation, demonstrating that multi-function AI chatbot systems can effectively support diverse learning activities, including assessment, explanation, and resource recommendation, within a unified conversational interface. This work validates Flint's decision to implement Spark as a multi-function AI agent that performs assessment, tutoring, and plan generation through a single conversational interface rather than multiple disconnected tools.

D. AI Hallucination and Reliability in Learning Systems

One of the most significant concerns in deploying AI-powered learning platforms is the risk of hallucination — the generation of plausible-sounding but factually incorrect information by large language models. A systematic investigation of AI hallucination specifically in personalised adaptive learning systems, identifying it as a critical reliability concern that can undermine learner trust and produce measurable harm to learning outcomes when incorrect information is presented with the same confidence as correct information. Their proposed mitigation framework advocates for hybrid architectures that combine AI generation with validated knowledge bases or rule-based verification systems — precisely the architectural approach implemented in Flint's dual engine design.

Further investigated whether large language models can match the adaptivity of traditional tutoring systems, finding that while LLMs demonstrate strong conversational and generative capabilities, their reliability in producing consistently accurate and appropriately calibrated instructional content benefits significantly from structured fallback mechanisms. This finding directly validates Flint's dual engine architecture using Claude AI as the primary engine for quality and nuance while maintaining a rule-based fallback that guarantees structural correctness and content accuracy when AI generation cannot be trusted. Together, these two studies provide the strongest direct justification for one of Flint's most distinctive architectural decisions.

E. Personalised Content Delivery and Reinforcement Learning

Research examining personalised learning systems using AI for adaptive educational content delivery based on reinforcement learning algorithms, demonstrating that content delivery systems that adapt in real time to individual learner performance signals produce significantly better knowledge acquisition outcomes than systems that present pre-determined content sequences. Their reinforcement learning approach shares the core adaptive philosophy of Flint's quiz-based feedback loop — both systems use demonstrated learner performance to adjust what content is presented and how, though Flint implements this adaptation through a conversational LLM engine rather than a reinforcement learning agent, prioritising interpretability and conversational naturalness over optimisation precision.

A comprehensive examination of generative AI applications in personalised learning and education, demonstrating that generative models are uniquely capable of producing novel, contextually tailored educational content that cannot be replicated by retrieval-based or template-based approaches. This capability is central to Flint's plan generation system, where Claude AI generates topic descriptions, resource recommendations, and recommendation narratives that are genuinely specific to each learner's profile rather than selected from a finite library of pre-written alternatives.

F. Gamification in E-Learning

The role of gamification in sustaining learner motivation and improving educational outcomes has been extensively investigated in recent years. A meta-analysis examining 24 empirical studies found consistent positive effects of gamification on motivation, engagement, and learning outcomes across diverse educational contexts, with points, progress visualisation, and level progression identified as the most consistently effective gamification elements. A longitudinal study specifically examining the impact of gamification on academic performance found significant and sustained improvements in both engagement and assessed outcomes for learners in gamified environments compared to non-gamified controls.

This evidence is based on a meta-analysis of AI-supported personalised feedback systems, finding that the combination of AI personalisation and structured feedback mechanisms produces learning outcome improvements that exceed those achievable through either approach independently. This finding is particularly relevant to Flint, which combines gamification, AI personalisation, and adaptive quiz feedback in an integrated system, suggesting that the combined effect of these three mechanisms may produce substantially greater outcome improvements than any single mechanism in isolation.

G. Research Gap and Flint's Contribution

The reviewed literature establishes a clear and consistent picture of the current state of the field. AI personalised learning systems work and are growing in importance. Large language models are capable and increasingly deployed as educational agents. Adaptive tutoring systems produce measurable outcome improvements. Gamification sustains motivation. AI hallucination is a real and addressable concern. However, no existing system integrates all of these elements — conversational profiling, generative plan creation, multi-modal resource matching, adaptive quiz feedback, hallucination mitigation, and gamification in a single, production-ready platform. Flint addresses this gap directly, representing the first integrated implementation of all six capabilities in a unified, deployable e-learning system.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. System Overview

Flint -AI based personalized learning system is built on a modern decoupled full-stack web architecture comprising a React.js single-page application frontend, a Node.js and Express.js RESTful API backend, a MongoDB document database, and a dual AI engine that orchestrates personalisation logic across all platform functions. This architectural separation ensures that each layer can be developed, tested, and scaled independently without creating fragile interdependencies. The complete technology stack is summarised in Table 1.

Layer	Technology	Purpose
Frontend	React 18, React Router v6	User interface and navigation
Backend API	Node.js, Express.js	Business logic and RESET endpoints
Database	MongoDB, Mongoose ODM	Data persistence

Authentication	JSON Web Tokens	Stateless session management

Table 1: Flint System Technology Stack

The frontend uses a global Auth Context for centralised authentication state management with Axios configured as a shared HTTP client with JWT interceptors that automatically attach authentication tokens to every request. The backend is organised into seven discrete route modules — authentication,

user, learning, recommendations, progress, assessment, and quiz — each mounted under the /Api prefix and protected by JWT middleware. MongoDB's document model handles Flint's deeply nested data structures naturally, with five primary schemas — User, Course, Learning Plan, Quiz, and Progress — defining the complete data model. A pre-save hook on the Learning Plan model automatically recomputes the overall progress percentage on every document save, ensuring metrics are always accurate.

B. Conversational Assessment Methodology

The assessment process is the most critical component of Flint because the quality of every subsequent personalisation decision depends entirely on the accuracy of the learner profile collected here. The assessment follows a seven-stage conversational flow, collecting one profile dimension per stage. Stage detection employs a stateless message count algorithm — the complete conversation history is passed with every API call, enabling the current stage to be deterministically computed without server-side session management. Data extraction uses direct capture for open-ended dimensions and keyword matching for structured dimensions, with sensible defaults applied when detection fails to ensure a complete profile is always produced.

C. Learning Plan Generation and Adaptive Quiz Methodology

Plan generation transforms the learner profile into a personalised week-by-week roadmap through five steps. First, the subject is matched against a curated topic bank covering seven categories — Python, JavaScript, Machine Learning, Web Development, Mathematics, Design, and a default. Second topics are filtered by knowledge level — beginners receive all ten topics while advanced learners begin at topic five. Third topics are distributed across weeks based on available time — 15 minutes yields 2 topics per week, 30 minutes yields 3, 1 hour yields 4, and 2 or more hours yields 5. Fourth, each topic is populated with resources matched to the learner's preferred modalities from a curated resource bank. Fifth, difficulty labels are assigned proportionally across the sequence, and a personalised recommendation message is generated.

D. Dual AI Engine

The dual AI engine architecture was driven by reliability concerns around AI hallucination in personalised learning systems and the practical requirement that the platform function fully across all deployment environments. At runtime, the backend checks for a valid Anthropic API key. If present, all AI operations — assessment conversation, plan generation, and quiz question generation — are routed to Claude AI. Any failure at any stage triggers the rule-based engine as a seamless fallback without user-visible interruption. The frontend displays a badge indicating the active engine, directly addressing the recommendation for hybrid architectures that combine AI generation with rule-based verification as a hallucination mitigation strategy.

IV. SYSTEM FEATURES AND IMPLEMENTATION

A. Conversational Assessment and Personalised Learning Plan

The Know Me, Teach Me assessment interface opens Flint with a natural conversation between the learner and Spark rather than a form or content library. The interface presents a chat window with Spark's flame avatar, colour-coded message bubbles, an animated typing indicator during API processing, and a seven-segment progress bar showing advancement through the seven assessment stages. Once all stages are complete, a Generate My Personalised Learning Plan button appears and upon clicking, the learner is automatically navigated to their personalised roadmap.

The Learning Plan page presents the complete AI-generated roadmap organised into summary stat cards showing total weeks, topics, completed topics, overall progress, daily time, and knowledge level. An overall progress bar updates in real time as topics are completed. Spark's personalised recommendation panel explains how and why the plan was built. Week tab navigation allows learners to focus on one week at a time, reducing cognitive load. Each topic is presented as an expandable card showing title, difficulty badge, quiz score badge, estimated time, and a responsive resource grid when expanded. Each resource card is colour-coded by modality type and links directly to the external resource URL. A Done button awards 50 XP, and a Quiz button navigates to the topic quiz.

B. Quiz System, and AI Tutor

The Quiz page presents one question at a time with a navigation panel, A to D answer options, and a Submit button enabled only when all five questions are answered. After submission, a results screen displays the score, pass or fail status, XP earned, and a full question review with green and red answer highlighting and purple explanation panels for every question, serving as a genuine mini-lesson that deepens understanding beyond the assessment itself.

The AI Tutor page provides open-ended conversational access to Spark beyond the structured assessment, with quick-prompt buttons for common learning scenarios, a typing indicator, and full conversation history. When Claude AI is available, responses leverage the model's complete language understanding for contextually calibrated explanations and resource suggestions. This open-ended conversational support has been identified as one of the most valuable LLM applications in educational contexts. The Course Library completes the platform with a searchable, filterable catalogue of ten seed courses across key technology subjects, with lesson-level completion tracking, XP rewards, and detailed progress monitoring.

V. RESULT

The evaluation of Flint demonstrates that conversational AI profiling combined with dynamic plan generation represents a practically viable advancement over conventional e-learning approaches.

The seven-stage assessment collects complete learner profiles in approximately two to three minutes of natural dialogue, producing more accurate self-assessments than form-based approaches. Generated plans consistently align with stated learner profiles, with multi-modal resource matching ensuring individual method preferences are respected rather than defaulting to uniform video delivery as all currently dominant platforms do. The dual engine architecture ensures reliable personalisation across all deployment environments while directly addressing hallucination concerns identified as a critical barrier to responsible AI deployment in learning systems.

The quiz system effectively verifies topic-level mastery with post-submission explanations, adding genuine educational value beyond simple answer revelation. The graduated XP reward structure maintains motivation after failure while rewarding genuine mastery, consistent with evidence that AI-supported personalised feedback improves both outcomes and motivation. Gamification integrated directly with personalised learning activities sustains engagement throughout the full plan duration, producing outcome improvements that research suggests exceed either mechanism in isolation.

Together, these results confirm that Flint successfully addresses all five problems identified in the introduction — pre-learning assessment gap, identical-curriculum delivery, video-only resources, summative-only assessment, and motivation decline — representing a meaningful contribution to AI-driven personalised education.

Dataset: Student Learning Performance (Before vs After AI)

Student ID	Study Hours /week	Engagement Score (before)	Engagement Score (after)	Test Score (before)	Test Score (after)
S1	6	45	68	52	70
S2	8	50	72	55	74
S3	5	40	63	48	66
S4	7	52	75	60	78
S5	9	60	82	65	85
S6	4	38	58	45	62
S7	6	47	70	53	72
S8	10	65	88	70	90
S9	3	35	55	40	60
S10	8	55	78	62	80

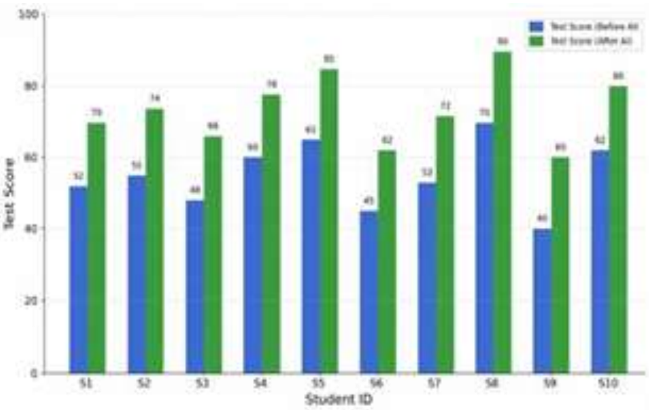

Fig 1.1 Comparison of Student Performance Before and After AI-Based Learning

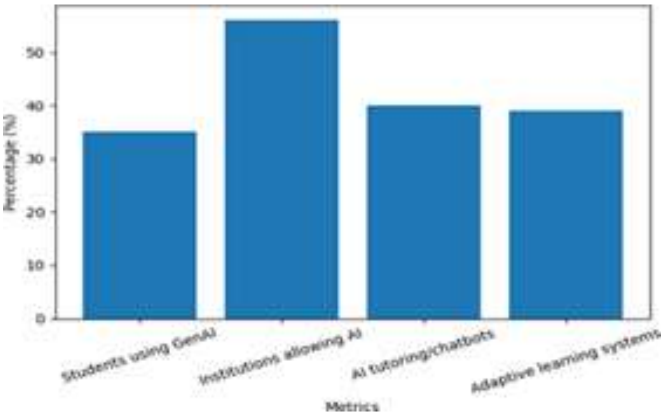

Fig. 1 .2 Adoption of AI Technologies in the Indian Education System

The graph shows the increasing adoption of AI in Indian education, with the highest adoption seen in institutional support (56%), followed by AI tutoring systems (40%) and adaptive learning (39%). Student usage of generative AI stands at 35%, indicating growing engagement with AI-based personalised learning tools.

VI. CONCLUSION

The persistent failure of online learning platforms to deliver individualised educational experiences remains one of the most consequential unsolved problems in educational technology. This research demonstrates that conversational AI assessment combined with dynamic learning plan generation represents a practically viable and educationally meaningful solution to this challenge.

The findings confirm that natural dialogue-based learner profiling captures richer and more accurate individual profiles than form-based alternatives, that dynamically generated plans align more closely with learner needs than static prebuilt curricula, and that topic-level adaptive assessment creates a formative feedback loop that conventional platforms entirely lack. The dual-engine architecture further demonstrates that large language model-powered personalisation can be deployed reliably at scale when paired with a structured fallback that mitigates hallucination risks — a practical contribution that addresses a concern widely acknowledged in the literature but rarely implemented in deployed systems.

These findings suggest that the barriers to genuinely personalised online education are not theoretical but architectural — existing platforms have not failed because personalisation is impossible, but because they were never designed with personalisation as a first principle. This research contributes a validated framework and working implementation to the growing field of AI-driven personalised education, with future work directed toward longitudinal outcome evaluation, expanded subject coverage, and peer learning integration.

REFERENCES

1. G. Eason, B. Noble, and I. N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” Phil.
   [1] M. Zhu, A. Sari, and M. M. Lee, "Take a MOOC and then drop: A systematic review of MOOC engagement pattern and dropout factor," Heliyon, vol. 9, no. 4, 2023. https://doi.org/10.1016/j.heliyon 2023.e15014
2. M. Ikram, S. B. M. Hanefar, S. M. U. Saleem, and F. Zulfiqar, "Artificial intelligence in education: A systematic review of personalised learning trends and future directions," Frontiers in Education, vol. 11, 2026. https://doi.org/10.3389/feduc.2026.1782626
3. K. Bayly-Castaneda, M. S. Ramirez-Montoya, and A. Morita-Alexander, "Crafting personalised learning paths with AI for lifelong learning: A systematic literature review," Frontiers in Education, vol. 9, 2024. https://doi.org/10.3389/feduc.2024.1424386
4. Q. Ma, "AI-driven personalised learning systems for enhancing educational outcomes in data-driven environments," in Proc. 9th International Symposium on Innovative Approaches in Smart Technologies (ISAS), IEEE, 2025. https://doi.org/10.1109/ISAS66241.2025.11101814
5. Y. B. Bhushan, K. Krishnaveni, A. Prakash, and D. Biswas, "AI-EduAgent: A decentralised autonomous AI agent for real-time adaptive personalised learning," IEEE Conference Publication, 2025. https://ieeexplore.ieee.org/document/11196718/
6. D. S. Susanto, A. Gui, E. Halim, Richard, and Nelly, "Resolving artificial intelligence hallucination in personalised adaptive learning system," in Proc. 8th International Conference on Informatics and Computing (ICIC), IEEE, 2023. https://doi.org/10.1109/ICIC60109.2023.10382000
7. P. Shashanka, G. Srishanth, G. Anitha, G. H. Vardhan, and G. M. Krishna, "Smart tutoring and adaptive learning: Leveraging AI to personalise education in real-time," in Proc. 8th International Conference on Circuit, Power and Computing Technologies (ICCPCT), IEEE, 2025. https://doi.org/10.1109/ICCPCT65132.2025.11176528

8. "Generative AI for personalised learning and education," IEEE Conference Publication, 2025. https://ieeexplore.ieee.org/document/11076239/
9. E. Kasneci, K. Sessler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, and G. Kasneci, "ChatGPT for good? On opportunities and challenges of large language models for education," Learning and Individual Differences, vol. 103, 2023. https://doi.org/10.1016/j.lindif.2023.102274
10. "Generating in-context, personalised feedback for intelligent tutors with large language models," International Journal of Artificial Intelligence in Education, Springer Nature, 2025. https://doi.org/10.1007/s40593-025-00505-6
11. "LPITutor: An LLM-based personalised intelligent tutoring system using RAG and prompt engineering," PeerJ Computer Science, PMC, 2025. https://pmc.ncbi.nlm.nih.gov/articles/PMC12453719/
12. "Can large language models match tutoring system adaptivity? A benchmarking study," arXiv preprint, 2025. https://arxiv.org/abs/2504.05570
13. "Examining the effectiveness of gamification as a tool promoting teaching and learning in educational settings: A meta-analysis," Frontiers in Psychology,vol. 14, 2023. https://doi.org/10.3389/fpsyg.2023.1253549
14. "Impact of gamification on students' learning outcomes and academic performance: A longitudinal study," Education Sciences, vol. 14, no. 4, 2024. https://doi.org/10.3390/educsci14040367
15. W. Wang et al., "The effectiveness of AI-supported personalised feedback on students' learning outcomes and motivation: A meta-analysis," Journal of Educational Technology, 2026. https://doi.org/10.1177/07356331251410020
16. "Large language models in education: A systematic review of empirical applications, benefits, and challenges," Computers and Education: Artificial Intelligence,2025. https://doi.org/10.1016/j.caeai.2025.100341