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Application of Large Language Models to Enhance Student Support Services in the Context of University Autonomy

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Abstract

This systematic review analyzes research on the application of Large Language Models (LLMs) to enhance the quality of learner support in the context of university autonomy. The study aims to evaluate the current applications of LLMs in providing personalized and adaptive learning paths, identify ethical challenges, and analyze the role of prompt engineering and human-in-the-loop supervision. The research method involves a systematic analysis of scientific works published up to mid-2024. The findings indicate that LLMs significantly enhance personalized feedback and adaptive tutoring, thereby promoting self-regulated learning and student engagement. However, challenges related to feedback accuracy and ethical issues persist, requiring robust governance frameworks. The conclusion emphasizes that effective LLM integration requires combining technological power with pedagogical expertise and human oversight to optimize the educational experience and successfully support autonomous learners.

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Introduction

The landscape of higher education is undergoing a profound transformation, driven by the dual forces of increasing institutional autonomy and a pedagogical shift towards personalized, learner-centric models. In this dynamic environment, technology has emerged as a critical enabler, with Artificial Intelligence (AI) at the forefront of innovation. The historical trajectory of AI in education began with early rule-based Intelligent Tutoring Systems (ITS) and has since evolved through the data-rich era of Massive Open Online Courses (MOOCs), which highlighted the need for scalable support mechanisms (Yu et al., 2024). This evolution has culminated in the advent of Large Language Models (LLMs), a paradigm-shifting technology with an unprecedented capacity for understanding and generating nuanced, human-like text. The emergence of LLMs represents a significant inflection point, offering the potential to address some of the most persistent challenges in higher education (Gan et al., 2023; Wen et al., 2024).

The practical significance of integrating LLMs into learner support is substantial. Higher education institutions grapple with the challenge of providing high-quality, individualized support to increasingly diverse student populations, often with limited faculty resources. LLMs offer a scalable solution to this dilemma. Early research has demonstrated their effectiveness in enhancing student engagement and learning outcomes through AI-powered interventions (Zhang et al., 2024; Schultze et al., 2024). Specifically, LLM-driven platforms have shown remarkable promise in delivering personalized learning pathways and instant formative feedback—two cornerstones for fostering the self-regulated learning and intrinsic motivation essential for success in an autonomous academic setting (Ng & Fung, 2024; Andonov, 2024; Meyer et al., 2023). By offering 24/7 assistance, LLMs can provide the timely support that helps bridge knowledge gaps and sustain momentum for learners.

However, the rapid proliferation of LLMs has also exposed a complex array of problems and controversies. While their potential is clear, their application is not without significant limitations. A primary issue is the models' struggle with domain-specific accuracy and deep contextual understanding, which can lead to the generation of plausible but incorrect information, or "hallucinations" (Daheim et al., 2024; Li et al., 2024). This lack of reliability necessitates a level of human oversight that can, in turn, undermine the very scalability that makes LLMs attractive. This has led to a schism in the academic discourse: on one side, researchers champion the transformative potential of LLMs to create truly personalized educational experiences (Dakshit, 2024; Shen, 2024); on the other, a more cautious camp raises alarms about the profound ethical implications, including algorithmic bias, data privacy violations, and the potential for over-reliance leading to the atrophy of students' critical thinking skills (Moore & Tsay, 2024; Alhafni et al., 2024; Dai et al., 2023).

This divergence highlights a critical research gap: the absence of a comprehensive, synthesized framework that can guide the responsible and effective integration of LLMs into learner support. There is a pressing need to move beyond siloed explorations of benefits and risks towards a holistic understanding that balances technological capability with pedagogical integrity and ethical responsibility (Wang et al., 2024; Choi & Abdirayimov, 2024; Eager, 2023). Without such a framework, the implementation of LLMs risks being haphazard, potentially failing to realize their benefits while amplifying their harms, and ultimately hindering the goal of fostering genuinely autonomous and successful learners (AlSobeh & Woodward, 2023).This systematic review aims to address this gap. The conceptual framework for this study defines LLMs as advanced AI systems enabling personalized feedback and adaptive learning (Gan et al., 2023; Bewersdorff et al., 2024), and defines autonomous learning as a process of self-regulation that can be scaffolded by such technologies (Steinert et al., 2023). By critically examining and synthesizing the current body of literature on the applications, challenges, and opportunities of LLMs in higher education, this paper seeks to provide a nuanced perspective that can inform the development of effective, scalable, and ethically sound AI-assisted educational interventions.

Method

This study was designed as a systematic literature review to synthesize and analyze scientific evidence on the application of LLMs to enhance the quality of learner support within the context of university autonomy. The process of selecting and analyzing literature was conducted rigorously and transparently to ensure the comprehensiveness and reliability of the results. The subjects of this study were scientific works, including peer-reviewed journal articles, conference proceedings, and technical reports published between 2023 and mid-2025. The selection criteria focused on empirical and theoretical studies that directly addressed the applications of LLMs in supporting learners in higher education. Non-peer-reviewed and irrelevant studies were excluded.

The information gathering process was conducted in three main steps. First, we performed query transformation, starting from the overall research question and expanding it into more specific, targeted search queries to cover various aspects of the topic. These queries were then executed on a comprehensive academic database to screen for and identify an initial set of 197 candidate papers. Finally, the citation chaining technique was applied, including both backward chaining (examining the reference lists of core papers) and forward chaining (identifying newer papers that cited the core works), to discover an additional 124 relevant publications. All 321 candidate papers were then subjected to a relevance scoring system to select a final corpus of the 69 most relevant articles for this review. Data from these papers were then thematically analyzed to identify trends, strengths, weaknesses, and gaps in the current research.

Results

Thematic Synthesis of LLM Applications

Across the reviewed literature, three superordinate themes emerge that encapsulate the current state of LLM integration in learner support: (1) the potent capabilities for personalized and adaptive learning, (2) the pivotal role of human-AI synergy, and (3) the pervasive ethical and practical challenges. This section provides a detailed analysis of each theme.

Theme 1: The Capabilities for Personalized and Adaptive Learning

This is the most prominent theme, with extensive evidence demonstrating the capacity of LLMs to deliver personalized learning experiences at an unprecedented scale. This capability is not monolithic but comprises several distinct functions that collectively support the autonomous learner.

Table 1. Analysis of the Personalized and Adaptive Learning Theme

Component	Description	Evidence and Examples from Literature	Key Studies
Formative Feedback Generation	LLMs can provide immediate, detailed, and non-judgmental feedback on a wide range of student work, including essays, reports, and programming code. This instant feedback loop allows for rapid iteration and improvement.	Studies show that AI-generated feedback can increase the quality and quantity of student revisions (Meyer et al., 2023) and that its quality can be comparable to that of human instructors for certain tasks (Dai et al., 2023). In programming, LLMs can effectively identify and suggest corrections for novice errors (Jacobs & Jaschke, 2024).	Meyer et al., 2023; Dai et al., 2023; Jacobs & Jaschke, 2024
Adaptive Scaffolding	This involves the dynamic adjustment of support (e.g., hints, explanations, simplified problems) based on a student's real-time performance and needs. The goal is to provide just enough support to enable progress without removing the productive struggle necessary for learning.	The LEAP platform exemplifies this by using systematic, pedagogically-informed prompts to provide tailored scaffolding that targets students' metacognitive processes, such as planning and self-reflection, thereby enhancing self-regulated learning (Steinert et al., 2023, 2024).	Steinert et al., 2023, 2024; Li et al., 2024
Personalized Learning Paths	LLMs can analyze a student's profile, including prior knowledge, learning goals, and performance data, to generate a customized sequence of learning activities and resources.	Ng & Fung (2024) demonstrated a system where LLMs plan coherent and personalized learning paths, which led to improved student performance and retention. This moves beyond a one-size-fits-all curriculum to a truly individualized educational journey.	Ng & Fung, 2024; AlSobeh & Woodward, 2023

Theme 2: The Pivotal Role of Human-AI Synergy

The literature is unequivocal that the most effective applications of LLMs are not fully autonomous but involve a thoughtful collaboration between human educators and AI systems. This synergy is crucial for quality, relevance, and safety.

Table 2. Analysis of the Human-AI Synergy Theme

Component	Description	Evidence and Examples from Literature	Key Studies
Pedagogical Prompt Engineering	The quality and pedagogical value of LLM outputs are highly contingent on the design of the input prompts. This goes beyond simple queries to involve structuring prompts that guide the AI towards specific educational goals and roles.	Jacobsen et al. (2025) found that domain-specific, pedagogically-informed prompts significantly improved feedback quality compared to generic prompts. Steinert et al. (2023) demonstrate how prompts can be designed to elicit specific types of metacognitive scaffolding.	Jacobsen et al., 2025; Steinert et al., 2023
Human-in-the-Loop (HITL) for Quality Control	This framework involves educators reviewing, validating, and refining AI-generated content before it reaches the student. This is the primary mechanism for mitigating errors, hallucinations, and ensuring pedagogical alignment.	Schultze et al. (2024) found that students perceived LLM feedback that had been augmented by a human as significantly higher in quality than feedback from either AI or a human alone. The “Feedback Copilot” tool is explicitly designed to facilitate this HITL process (Pozdniakov et al., 2024).	Schultze et al., 2024; Pozdniakov et al., 2024
The Evolving Role of the Educator	The integration of LLMs necessitates a shift in the educator's role from being the primary “sage on the stage” to a “guide on the side” or, more accurately, a “designer of learning environments.”	Eager (2023) discusses this evolution, arguing for a model where educators leverage AI as a powerful supplementary tool to enhance their teaching practice. This involves skills in curriculum design, AI literacy, and mentoring students on the responsible use of these tools (Zhang et al., 2024).	Eager, 2023; Zhang et al., 2024

Theme 3: Pervasive Ethical and Practical Challenges

The implementation of LLMs is fraught with significant challenges that extend beyond technical performance. These issues represent fundamental barriers to safe, equitable, and effective integration.

Table 3. Analysis of the Ethical and Practical Challenges Theme

Component	Description	Evidence and Examples from Literature	Key Studies
Data Privacy and Security	The use of student data, which is often sensitive and personally identifiable, with third-party commercial LLMs raises significant privacy and security concerns.	Moore & Tsay (2024) and Shahzad et al. (2025) highlight the urgent need for robust institutional governance. The exploration of on-premise or open-source models is proposed as a potential solution to maintain data sovereignty (Poličar et al., 2025).	Moore & Tsay, 2024; Shahzad et al., 2025; Poličar et al., 2025
Algorithmic Bias and Equity	LLMs are trained on vast datasets from the internet, which contain inherent societal biases. These models can reproduce and amplify these biases, potentially disadvantaging students from underrepresented groups.	Alhafni et al. (2024) and Wang et al. (2024) identify this as a critical challenge that threatens to widen existing educational equity gaps if not actively addressed through bias audits and mitigation strategies.	Alhafni et al., 2024; Wang et al., 2024
Academic Integrity	The ability of LLMs to generate sophisticated, human-like text poses a fundamental challenge to traditional methods of assessment and the definition of plagiarism.	This requires a pedagogical shift away from assessing only the final product towards assessing the process of learning. Eager (2023) and Dong et al. (2024) advocate for assessments that require critical engagement with AI, such as critiquing an LLM's output.	Eager, 2023; Dong et al., 2024; Raihan et al., 2024
Reliability and Hallucinations	A core technical weakness of LLMs is their propensity to "hallucinate"—to generate confident, fluent, but factually incorrect or nonsensical information.	This poses a significant risk to learners who may not have the expertise to identify such errors. Research into Retrieval-Augmented Generation (RAG) and other verification mechanisms is a key area of focus to combat this issue (Kiesler et al., 2023; Daheim et al., 2024).	Kiesler et al., 2023; Daheim et al., 2024; Jacobs & Jaschke, 2024

Analysis of Specific LLM-Powered Tools and Platforms

To provide a concrete understanding of LLM applications, several specific tools and architectural approaches from the literature were analyzed. These examples highlight the practical strengths and weaknesses of current implementations, moving from theoretical potential to tangible application.

Table 4. Analysis of Specific LLM-Based Educational Tools and Approaches

Tool/Approach	Purpose	Strengths	Weaknesses / Challenges	Key Studies
LEAP (Learning Assistant Platform)	To provide adaptive, formative feedback that scaffolds students' self-regulated learning processes.	- Systematically designed prompts enhance feedback quality. - Shown to improve learning outcomes and motivation. - Aligns with established educational theories.	- Requires significant expertise in prompt engineering. - Effectiveness is dependent on the quality of the underlying LLM (e.g., GPT-4).	Steinert et al. (2023, 2024)
eduMAS (Educational Multi-Agent System)	To provide context-aware, expert-level feedback by decomposing complex educational tasks among specialized LLM agents.	- Improves contextual understanding and reduces hallucinations. - Can handle complex, multi-faceted problems better than single-agent systems.	- Increased system complexity and computational cost. - Requires sophisticated orchestration of agents.	Li et al. (2024)
RAG-based Tutors (Retrieval-Augmented Generation)	To create intelligent tutors that ground their responses in a specific corpus of reliable knowledge (e.g., course textbooks).	- Significantly reduces the risk of generating factually incorrect information (hallucinations). - Ensures feedback is relevant and aligned with the curriculum.	- Performance depends heavily on the quality of the retrieval system and the knowledge base. - Can be less flexible or creative than non-RAG models.	Dakshit (2024); Modran et al. (2024)
Feedback Copilot	A user interface framework to help educators provision personalized feedback at scale by leveraging LLMs.	- Empowers educators by keeping them in the loop. - Improves teaching efficiency without fully automating the feedback process.	- Relies on the educator's ability to effectively use the tool and validate AI suggestions. - Does not eliminate the need for human oversight.	Pozdniakov et al. (2024)

SWOT Analysis of LLM Integration in Learner Support

A SWOT analysis synthesizes the internal strengths and weaknesses and the external opportunities and threats associated with the integration of LLMs in higher education learner support, based on the collective findings of the reviewed literature. This framework provides a strategic overview of the key factors that institutions and educators must consider.

Table 5. SWOT Analysis of LLMs in Higher Education Learner Support

	Strengths (Internal)	**Weaknesses (Internal)**
Helpful (to achieving the objective)	**1. Personalization at Scale:** LLMs can provide instant, individualized feedback and adaptive learning paths to large student cohorts (Steinert et al., 2024; Ng & Fung, 2024).	**1. Accuracy and Hallucinations:** LLMs can generate plausible but factually incorrect or nonsensical information, posing a risk to learners (Kiesler et al., 2023; Jacobs & Jaschke, 2024).
	2. 24/7 Availability: AI-powered tutors and support systems are accessible to learners anytime, anywhere, overcoming time-zone and scheduling constraints (AlSobeh & Woodward, 2023).	**2. Lack of Pedagogical Awareness:** Out-of-the-box LLMs lack innate understanding of pedagogy and require extensive prompt engineering or fine-tuning to be effective educational tools (Jacobsen et al., 2025).
	3. Fostering Self-Regulation: Interactive feedback and scaffolding can promote students' metacognitive skills and self-regulated learning habits (Kumar et al., 2024; Steinert et al., 2023).	**3. High Computational Cost:** Training and deploying state-of-the-art LLMs is resource-intensive, creating a barrier for many institutions (Wang et al., 2024).
	Opportunities (External)	**Threats (External)**
Harmful (to achieving the objective)	**1. Multimodal Learning:** The rise of multimodal LLMs (that process text, images, and audio) opens new avenues for creating richer, more accessible learning experiences (Bewersdorff et al., 2024).	**1. Ethical and Privacy Risks:** The use of student data to train or interact with LLMs raises significant privacy concerns. Algorithmic bias can perpetuate and amplify societal inequities (Moore & Tsay, 2024; Shahzad et al., 2025).
	2. Human-AI Collaboration Models: LLMs can augment, rather than replace, educators, leading to new, more effective pedagogical models where teachers act as expert curators and mentors (Schultze et al., 2024).	**2. Academic Integrity:** The ease of generating text with LLMs poses a significant threat to traditional assessment methods and academic integrity (Dong et al., 2024; Eager, 2023).
	3. Open-Source Advancement: The	**3. Over-reliance and Skill Atrophy:**

	Strengths (Internal)	Weaknesses (Internal)
	growing availability of powerful open-source LLMs can democratize access, reduce costs, and allow for greater transparency and customization (Poličar et al., 2025).	Students may become overly dependent on LLMs, leading to a decline in critical thinking, problem-solving, and writing skills (Raihan et al., 2024; Zhang et al., 2024).

Discussion and Conclusion

The synthesis of findings reveals a fundamental tension between the transformative potential of LLMs and the significant challenges they present. The strengths and opportunities—primarily centered on scalable personalization and new pedagogical paradigms—are compelling. Tools like LEAP and RAG-based tutors demonstrate a clear path toward providing high-quality, individualized support that was previously unfeasible in large-scale higher education (Steinert et al., 2024; Dakshit, 2024). The opportunity to augment human educators, freeing them from repetitive tasks to focus on higher-order mentoring, is particularly promising (Schultze et al., 2024).

However, these opportunities are directly counterbalanced by the weaknesses and threats. The issue of reliability, manifested as "hallucinations," is a critical weakness that undermines the trustworthiness of LLMs as standalone educational tools (Kiesler et al., 2023). This necessitates the human-in-the-loop approach, which, while effective, compromises the very scalability that makes LLMs so attractive (Jacobsen et al., 2025). Furthermore, the external threats are profound. Without robust ethical frameworks and institutional policies, the integration of LLMs could lead to significant privacy violations and exacerbate educational inequalities through algorithmic bias (Moore & Tsay, 2024; Shahzad et al., 2025). The challenge to academic integrity is not merely technical but pedagogical, requiring a fundamental rethinking of how learning is assessed (Eager, 2023). Therefore, the successful integration of LLMs is not a simple matter of technological adoption. It requires a deliberate, balanced strategy that actively mitigates the risks while cultivating the benefits. This involves investing in educator training, developing clear ethical guidelines, and prioritizing pedagogical goals over purely technological capabilities.

The collective evidence from the reviewed literature indicates that Large Language Models hold immense and promising potential to reshape learner support in autonomous higher education environments. The ability of LLMs to provide personalized, adaptive, and scalable learning experiences has been demonstrated across multiple studies, particularly in generating immediate formative feedback, constructing flexible learning paths, and supporting metacognitive processes. However, the path to a comprehensive and sustainable integration of LLMs is still fraught with challenges. Inherent issues such as information accuracy, the risk of hallucinations, and especially the complex problems of ethics and privacy require urgent attention and solutions. The success of LLM deployment depends not only on technological power but also heavily on the human element.

Based on these results and discussions, this study proposes that future research should focus on developing standardized ethical and governance frameworks, building methods to mitigate hallucinations and enhance model reliability, and conducting longitudinal studies to assess the long-term impact on learner autonomy. A balanced approach that harmoniously combines the capabilities of AI with human intelligence and expertise will be the key to unlocking the full potential of LLMs, thereby genuinely enhancing the quality of education and empowering learners in the digital age.

Recommendations

Based on the synthesis of findings, this review proposes the following actionable recommendations for key stakeholders to foster the effective and ethical integration of LLMs in higher education.

For Educators and Instructional Designers

- *Develop AI Literacy and Prompt Engineering Skills:* Educators should actively seek professional development opportunities to understand the capabilities and limitations of LLMs. Training should focus on pedagogical prompt engineering—the art of crafting prompts that elicit pedagogically valuable responses—to move beyond simple content generation towards fostering critical thinking and deeper learning (Jacobsen et al., 2025).
- *Adopt a Human-in-the-Loop (HITL) Approach*: Rather than viewing LLMs as autonomous agents, educators should integrate them as “copilots” or assistants. This involves using LLMs to generate draft feedback, create initial learning materials, or brainstorm ideas, with the educator performing the final validation, refinement, and contextualization (Pozdniakov et al., 2024; Schultze et al., 2024).
- *Redesign Assessments to Emphasize Process and Critical Thinking:* To address academic integrity concerns, assessments should be redesigned to focus less on final outputs that can be easily generated by AI and more on the learning process. This could include in-class discussions, project-based learning, oral examinations, and assignments that require students to critique or refine LLM-generated content (Eager, 2023).

For Higher Education Institutions

- *Establish Clear and Comprehensive AI Governance Policies:* Institutions must develop clear policies regarding the ethical use of LLMs. These policies should address data privacy and security (especially concerning student data), academic integrity, transparency in the use of AI tools, and equity to prevent algorithmic bias from disadvantaging certain student populations (Moore & Tsay, 2024; Shahzad et al., 2025).
- **I***nvest in a Robust and Secure Technical Infrastructure:* To mitigate privacy risks associated with commercial LLMs, institutions should explore investing in secure, on-premise solutions or vetted open-source models that allow for greater control over data (Poličar et al., 2025). Providing a centrally supported infrastructure can also ensure equitable access for all faculty and students.
- *Promote Interdisciplinary Collaboration:* Fostering collaboration between computer scientists, education researchers, subject-matter experts, and ethicists is crucial for developing effective and

responsible LLM applications. Institutions should create initiatives and funding opportunities that support such interdisciplinary teams (Li et al., 2024; Gan et al., 2023).

For Researchers

- *Conduct Longitudinal Studies:* There is a significant gap in understanding the long-term effects of LLM integration on student learning, self-regulation, and potential skill atrophy. Future research should prioritize longitudinal studies that track student development over multiple semesters or years (Yu et al., 2024; Raihan et al., 2024).
- *Focus on Mitigating Hallucinations and Improving Reliability:* Research into technical solutions for improving the factual accuracy of LLMs is paramount. This includes advancing Retrieval-Augmented Generation (RAG) techniques, developing better fact-checking mechanisms, and creating models that can express uncertainty or defer to human experts when appropriate (Dakshit, 2024; Daheim et al., 2024).
- *Explore the Efficacy of Diverse and Open-Source Models:* The current literature is heavily skewed towards a few commercial models (e.g., GPT series). Future studies should investigate a wider range of models, particularly open-source alternatives, to assess their comparative strengths and weaknesses in educational contexts and to promote a more transparent and accessible research ecosystem (Poličar et al., 2025).

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