International Research Journal of Multidisciplinary Scope (IRJMS), 2026; 7(2): 213-226

Original Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2026.v07i02.09619

Over-reliance on Large Language Models in Higher Education: Ethical and Institutional Challenges in Responsible AI Integration

Vengalarao Pachava[1], Olusiji Adebola Lasekan[2]*,
Margot Teresa Godoy Pena[3], Kotigari Reddi Swaroop[4], Sunitha Guniganti[5]

[1]Department of Management, Nalsar University of Law, Hyderabad-500101, Telangana, India, [2]Departamento de Educación e Innovación, Universidad Católica de Temuco, Temuco-4780000, Chile, [3]Languages Coordination, Dirección de Trayectoria Formativa, Universidad de La Frontera, Temuco-4780000, Chile, [4]Entrepreneurship Development Institute of India, Ahmedabad, Gujarat-382428, India, [5]Department of Management Studies, National Institute of Technology, Warangal-506004, Telangana, India.

*Corresponding Author's Email: olasekan@uct.cl

Abstract

The integration of Large Language Models (LLMs) such as ChatGPT in higher education presents both transformative opportunities and critical pedagogical challenges. This study examines the motivations, behaviors, and contextual factors that contribute to students' over-reliance on LLMs, with particular attention to cognitive, social, and institutional dynamics. Adopting a qualitative research design grounded in Root Cause Analysis (RCA), the study draws on guided interviews with undergraduate students across professional disciplines. Five interrelated themes emerged: LLMs as learning substitutes, time pressure and efficiency seeking, normalization through peer influence, ethical ambiguity and misuse, and institutional gaps in support and guidance. While LLMs enhance accessibility and efficiency, findings indicate that excessive reliance encourages cognitive offloading, weakens critical thinking, and reshapes students' learning practices toward surface-level engagement. The study further reveals limited institutional preparedness, characterized by inadequate faculty development, minimal ethical training, and the absence of clear policies governing AI use. Peer norms and competitive academic cultures further reinforce reliance on LLMs as normalized practice. In response, the study proposes policy, pedagogical, and institutional reforms aimed at promoting ethical AI literacy, critical engagement, and equitable access. By foregrounding students' lived experiences, this research contributes to the growing discourse on digital transformation in higher education and underscores the need to align LLM integration with responsible learning practices that strengthen intellectual autonomy and academic integrity.

Keywords: AI Ethics, Critical Thinking, Educational Policy, Higher Education, Large Language Models.

Introduction

Artificial Intelligence (AI) is increasingly becoming a pivotal component in higher education, transforming teaching, learning, and administrati ve processes. The rapid integration of AI tools—particularly Large Language Models (LLMs) like ChatGPT—has redefined academic engagement by enabling personalized learning experiences, streamlining institutional operations, and support ing data-driven decision-making. Intelligent tutoring systems and adaptive platforms tailor educational content to individual student needs, while AI-driven tools provide immediate feedback, encourage deeper inquiry, and enhance learning strategies (1, 2). In disciplines such as law, AI supports problem-solving and academic performance through targeted feedback (3). On the administrative front, AI automates grading, admissions, and scheduling tasks, thereby improving institutional efficiency and strategic planning (4, 5). However, the benefits of AI integration are accompanied by ethical and social concerns, including risks to academic integrity, data privacy, and critical thinking (6, 7). Moreover, unequal access to AI technologies and limited digital literacy may exacerbate educational inequalities (8). As AI continues to influence curriculum design and pedagogy, there is a growing need for faculty training and ethical frameworks to guide its responsible use (1, 5). AI must be harnessed not only for innovation but also for promoting equitable and quality education. This study contributes to that objective by

(Received 10th December 2025; Accepted 06th March 2026; Published 02nd April 2026)

exploring the root causes of student over-reliance on LLMs in higher education, using qualitative interviews and root cause analysis to uncover the interplay between behavioral, social, and institutional factors shaping students' use of AI in academic contexts.

The integration of innovative technologies, particularly Artificial Intelligence (AI), into education has ushered in a new era of transformative possibilities. From personalized learning to global accessibility, AI offers powerful tools to enhance teaching, streamline administrative processes, and make education more inclusive and responsive. Among the most celebrated benefits is AI's ability to personalize learning experiences through intelligent tutoring systems and adaptive platforms that tailor content to student needs, boosting engagement and academic outcomes (9, 10). Innovative pedagogical strategies like gamification, project-based learning, and flipped classrooms—often supported by digital tools—have further transformed traditional classrooms into interactive spaces that promote motivation and participation (11). Additionally, AI contributes to administrative efficiency by automating tasks such as grading and scheduling, allowing educators more time to focus on instruction (9). Its role in expanding global accessibility is also significant, providing educational opportunities for learners in remote, underserved, and differently-abled communities (12). However, these advancements are not without pitfalls. Ethical concerns related to data privacy, algorithmic bias, and consent demand robust safeguards (10, 13). The persistent digital divide threatens to widen educational inequalities, leaving marginalized students behind (12). Furthermore, over-reliance on AI may erode critical thinking, reduce the human dimension of teaching, and diminish the role of educators (14, 15). Job displacement is another growing concern as automation increasingly takes over tasks traditionally performed by educators and staff (12). To ensure AI enhances rather than undermines education, it is essential to strike a balance between technological innovation and educational integrity. This paper explores the dual realities of promise and risk in the use of AI in education, offering insights into how innovation can be responsibly integrated without compromising core educational values.

As Artificial Intelligence (AI) becomes increasingly embedded in educational systems, the need to ensure its reliability, ethical use, and effectiveness grows ever more urgent. Root Cause Analysis (RCA), a method traditionally used in engineering and healthcare, offers a powerful tool for addressing the complexities and potential failures inherent in AI-integrated learning environments. Unlike approaches that focus on individual errors, RCA emphasizes the identification of systemic and procedural flaws, making it particularly relevant in educational contexts where the implications of failure affect student learning outcomes, data privacy, and equity (16). With AI systems relying on vast datasets and algorithms, challenges such as mislabeled or insufficient training data can undermine performance and exacerbate bias. Recent advances in RCA methodologies—such as decision-tree models, unsupervised and semi-supervised learning, and frequent-pattern mining—offer innovative ways to detect, analyze, and correct systemic issues in AI applications (17). These techniques allow institutions to diagnose failures with greater accuracy and design more robust systems that support both ethical principles and improved educational outcomes. Moreover, RCA contributes to building trust in AI technologies by exposing root causes of algorithmic bias or unintended behaviors, enabling the design of fairer, more transparent, and accountable systems (12, 18). As educational institutions increasingly rely on AI to personalize learning, automate assessments, and manage student data, RCA becomes essential for safeguarding quality and equity in digital education (19). This paper explores the central role of RCA in AI-integrated learning, analyzing both technical and ethical implications, and advocating for its broader adoption as a foundational practice in educational innovation.

Root Cause Analysis (RCA) was selected for this study because it enables systematic examination of complex, multi-level educational phenomena by tracing observable behaviors back to their underlying structural and procedural origins. Unlike conventional qualitative approaches that primarily emphasize meaning-making or theory construction, RCA is explicitly diagnostic in orientation, making it particularly suitable for investigating AI-related learning challenges that emerge from interacting cognitive, social, and institutional factors.

The objective of this study is to investigate the behavioral, motivational, social, and institutional dimensions underlying students' use of Large Language Models (LLMs) in higher education, with a particular focus on patterns that indicate over-reliance. By exploring how students describe their use of LLMs in academic tasks, the study aims to identify motivations and behaviors that may reflect a substitution of critical thinking with AI-generated content. It further seeks to examine the perceived root causes of this reliance, the influence of peer norms and academic culture, and the extent to which students feel supported or guided by faculty and institutional policies. Understanding the root causes of over-reliance through a qualitative lens and Root Cause Analysis (RCA) provides actionable insights for designing informed interventions, promoting responsible AI use, and fostering critical engagement in AI-enhanced academic environments. By applying RCA to qualitative student narratives, the study moves beyond documenting LLM usage to theorizing the systemic conditions that produce AI dependency in higher education.

In this study, "over-reliance" is operationally defined as the use of LLMs in ways that replace essential cognitive learning processes—such as critical thinking, synthesis, problem-solving, and reflective engagement—rather than supporting them. Productive LLM use is understood as complementary engagement, including clarificatio n of concepts, brainstorming, or feedback that enhances independent reasoning. Over-reliance, by contrast, occurs when students depend on AI-generated outputs as primary learning agents, leading to cognitive offloading and surface-level engagement (20).

The integration of Large Language Models (LLMs) such as ChatGPT in higher education has introduced transformative possibilities alongside complex challenges. These AI tools are increasingly used by students and educators to support a range of academic tasks, including writing assistance, coding, assessment, and even behavioral simulation. In writing, LLMs help generate content, summarize sources, and structure arguments, enhancing students' writing quality (21, 22). In computer science, they facilitate code generation and debugging, translating natural language instructions into programming solutions (23). They also assist in assessment by automating grading and providing real-time feedback, improving instructional efficiency (24), while in psychology, LLMs simulate human behavior to aid understanding of cognitive processes (22). These applications contribute to personalized learning experiences and allow educators to focus on more interactive teaching methods (24). Additionally, LLMs may foster critical thinking by exposing students to multiple perspectives and problem-solving approaches (25). However, growing concerns about academic integrity, such as plagiarism and task outsourcing, suggest that students may rely on LLMs in ways that hinder genuine skill development (21). Ethical issues related to transparency, data privacy, and responsible AI use further complicate their integration in education (26). Moreover, overdependence on these tools may impede the cultivation of core academic competencies. To address these concerns, scholars emphasize the need for faculty-led training and clear institutional guidelines that ensure AI tools are used in ways that align with educational objectives (21, 26). Future research must also explore the long-term effects of LLMs on teaching and learning, balancing innovation with ethical oversight and inclusive pedagogy (25).

The integration of artificial intelligence (AI) in educational contexts has prompted a growing discourse on its impact on students' critical thinking skills. While AI tools such as ChatGPT offer unprecedented access to information and personalized learning, their influence on cognitive engagement remains a significant concern. One key issue is the dependency on AI tools, where students increasingly rely on AI-generated responses without applying independent judgment, potentially stifling reasoning and creativity (27). This phenomenon, often described as cognitive offloading, reduces students' capacity to process and evaluate content critically (28). Additionally, the superficial engagement fostered by many AI platforms, which often provide quick answers devoid of conceptual depth, leads to shallow learning and the imitation of AI reasoning patterns rather than the development of personal analytical frameworks (27). Compounding the issue is the lack of pedagogical adaptation; traditional instructional models such as Bloom's

Taxonomy fall short in addressing the nuanced demands of AI-assisted learning, calling for revised frameworks that integrate competencies like ethical scrutiny and reflective questioning (29). Ethical and cognitive dimensions also emerge, as students must learn to interrogate the accuracy and bias of AI outputs—skills crucial for navigating misinformation and fostering digital discernment (30). To mitigate these challenges, scholars advocate for educational strategies and interventions that promote active, inquiry-based learning. Field visits, seminars, and workshops have been shown to enhance critical thinking by encouraging students to reflect, justify their viewpoints, and interact meaningfully with real-world issues (31). Ultimately, the literature underscores the need for pedagogical models that integrate AI tools without compromising students' intellectual independence, ensuring that AI becomes a catalyst—not a constraint—for deeper cognitive engagement and critical thought (31, 32).
Peer norms and social behavior play a pivotal role in shaping educational outcomes by influencing students' attitudes, actions, and interpersonal dynamics within academic environments. As shared expectations guiding behavior within peer groups, peer norms significantly affect both prosocial and antisocial behaviors, thereby shaping the social and academic climate of educational institutions. Studies show that positive peer norms enhance cooperation, empathy, and inclusivity, while negative norms may reinforce aggression and exclusion. For instance, supportive peer environments have been associated with increased prosocial behaviors and reduced antisocial tendencies through improved intergroup contact (33). In specialized classroom contexts, such as those for students with emotional and behavioral disorders, classroom norms have been found to predict individual behaviors, underscoring their influence on behavioral outcomes (34). Moreover, peer norms are also linked to risk-taking, with evidence suggesting that exposure to norms discouraging risky behavior can foster safer decision-making among students (35). The broader social context, including classroom dynamics and school climate, further shapes how peer norms function. Likewise, shifts in aggressive and prosocial peer norms have been shown to directly predict corresponding changes in adolescents' behavior over time, underscoring how classroom norm climates actively shape students' social conduct (36). While a positive school climate was associated with improved intergroup behavior and reduced ethnic conflict (37). Peer norms also vary in development and stability, with descriptive norms (group averages) showing more stability, while status norms (linked to popularity or leadership) are more fluid and context-dependent (38). In South Korea, students' behaviors were shaped by status norms associated with admired or popular peers (39). Also, adolescents often conformed to majority or high-status peer expectations in forming personal normative evaluations (40). These findings have significant educational implications, suggesting that interventions leveraging peer norms can promote positive behavior, enhance classroom relationships, and reduce conflict. Strategies such as group contingencies and targeted support programs have shown promise in improving social functioning, particularly among students facing behavioral challenges (34). Furthermore, school-based peer network interventions have proven effective in promoting prosocial behavior across divided or multicultural settings (33).

Methodology

This study adopted a qualitative research design grounded in interpretivism and informed by constructivist learning theory to explore how professional students perceive, experience, and negotiate the integration of Large Language Models (LLMs) within their academic and professional learning. The interpretivist paradigm was selected to enable deep exploration of the subjective meanings, contextual nuances, and domain-specific practices through which students appropriate LLM technologies (41, 42). Constructi vist learning perspectives further informed the study design, recognizing students as active agents who shape and co-construct their learning experiences with AI tools, rather than passive recipients of technological affordances (43).
While qualitative approaches such as phenomenology focus on lived experience and grounded theory emphasizes emergent theoretical development, RCA was chosen because the study's primary objective was to identify the systemic conditions that produce student over-reliance on LLMs (44). RCA facilitates movement from descriptive accounts to causal explanation by

mapping relationships among individual behaviors, peer norms, curriculum design, and institutional practices. This makes it especially appropriate for examining AI dependency as a socio-technical issue rather than an isolated student behavior.

Participant Selection

Purposive sampling was employed to recruit information-rich participants who could provide detailed insights based on substantial experience with LLM use for academic purposes. Eligibility criteria required that participants be senior undergraduate or postgraduate students who had used LLMs (e.g., Chat GPT, Gemini, Copilot, Claude) at least five times in their academic work. To ensure a diverse sample and capture variations across disciplinary cultures, maximum variation sampling was used with attention to gender and domain of study.

The final sample comprised 19 students (12 female, 7 male) drawn from four metropolitan universities in India. This multi-institutional sampling enabled comparison of peer norms and academic pressures across professional domains and institutional environments. Participants represented four professional domains: Engineering, Pharmacy, Management, and Law fields in which discipline-specific dynamics around LLM adoption are increasingly salient (45-48).

Participant Demographics

Table 1 presents an overview of the 19 participants, including respondent code, academic domain, and gender. This diversity enabled rich exploration of both shared and discipline-specific experiences.

Table 1: Participant Demographics

Respondent Code	Domain	Gender
R1	Engineering	Male
R2	Engineering	Female
R3	Engineering	Male
R4	Engineering	Male
R5	Pharmacy	Female
R6	Pharmacy	Male
R7	Pharmacy	Female
R8	Pharmacy	Female
R9	Pharmacy	Female
R10	Pharmacy	Male
R11	Management	Male
R12	Management	Male
R13	Management	Female
R14	Management	Female
R15	Law	Female
R16	Law	Female
R17	Law	Female
R18	Law	Male
R19	Law	Male

Data Collection

Semi-structured interviews were conducted between November and December 2024. Interviews were conducted in-person (n = 12) or via secure video conferencing (n = 7), according to participant preference. Each interview lasted approximately 45–60 minutes, was conducted in English, audio-recorded with informed consent, and transcribed verbatim.

The interview guide was developed through a synthesis of insights from recent literature on AI in education (26, 41, 42). It was designed to elicit rich, open-ended accounts of students' evolving relationships with Large Language Models (LLMs). It focused on six core areas: patterns of LLM use in academic and professional preparation tasks; motivations behind over-reliance on LLMs for learning; perceived root causes for substituting critical thinking with AI-generated content; the influence of social norms and peer behavior on students' attitudes toward LLM use; and students' perceptions of the support and guidance provided by faculty and institutions in promoting responsible use of LLMs. Consistent with the constructivist orientation of the study, questions were open-ended and exploratory, allowing participants to foreground issues and perspectives salient to their own experiences.

Ethical Considerations and Researcher Reflexivity

Verbal ethical approval for the study was obtained from the host institution. Participation was voluntary, and informed consent was secured prior to interviews. Participants were assured that their responses would remain confidential and would have no bearing on academic evaluation. To minimize power asymmetries, interviews were conducted by researchers who were not involved in participants' teaching or assessment. All data were anonymized using coded identifiers.

Recognizing the potential influence of researcher positionality, the research team engaged in reflexive practices throughout data collection and analysis. As scholars working in higher education, we acknowledge that our perspectives on AI integration may shape interpretation. To mitigate this, reflexive memoing, team-based coding, and iterative discussion were employed to challenge assumptions and enhance analytic rigor.

Data Analysis

Data were analyzed using thematic analysis, following six-phase framework: familiarization with the data (49); generation of initial codes; searching for themes; reviewing themes; defining and naming themes; and producing the final report. Thematic analysis was selected for its flexibility and transparency in enabling rich, inductive interpretation of complex qualitative data (50). Two members of the research team independently conducted initial coding using ProVise qualitative analysis software to facilitate systematic data management and interrogation. An inter-coder agreement of 87% was reached after iterative discussion and reconciliation of coding differences.

Thematic analysis was first employed to identify recurring patterns in student narratives (51). RCA was then applied as a second analytic layer using Fishbone Diagram logic and the 5 Whys technique to trace these themes to their underlying cognitive, pedagogical, social, and institutional drivers. This sequential approach enabled the study to move beyond thematic description toward identifying systemic leverage points for educational intervention.

Over-reliance was identified analytically through recurring behavioral indicators in participant narratives, including substitution of independent thinking with AI outputs, passive acceptance of generated content, assignment outsourcing, and reduced engagement with course materials. These criteria guided thematic coding and informed the Root Cause Analysis.

Claims related to cognitive offloading were grounded in recurring behavioral indicators across interviews, including students' descriptions of replacing independent reasoning with AI-generated outputs, passive acceptance of responses without verification, assignment outsourcing, and reduced engagement with primary learning materials. These indicators were triangulated with Root Cause Analysis outputs to connect individual behaviors with broader curricular, institutional, and peer influences.

A hybrid coding approach was employed. Deductive codes were drawn from the study's conceptual framing (e.g., ethical concerns, discipline-based practices, professional identity), while inductive coding foregrounded emergent insights from participants' narratives. Codes were refined through iterative comparison, memoing, and clustering, resulting in a final thematic structure that captured both cross-cutting patterns and domain-specific dynamics in students' experiences of LLM integration.

Following the thematic analysis, a Root Cause Analysis (RCA) was conducted to further investigate the systemic drivers behind the five emergent themes. The RCA incorporated both the Fishbone Diagram logic and the 5 Whys technique to trace how cognitive, institutional, social, and pedagogical factors contributed to students' over-reliance on LLMs. To support visual clarity and analytical depth, the Matplotlib Python ChatGPT plugin was used to generate color-coded Fishbone diagrams. These visualizations served as both analytic tools and illustrative figures, offering a concise representation of the root causes and interconnections embedded in the data.

Results

This study analyzed qualitative interview responses from five university students across disciplines to explore how and why students rely on Large Language Models (LLMs) for academic work. Using thematic analysis and Root Cause Analysis (Fishbone and 5 Whys), five core themes emerged: (a) LLMs as Learning Substitutes, (b) Time Pressure and Efficiency Seeking, (c) Normalization and Peer Influence, (d) Ethical Ambiguity and Misuse and (e) Lack of Institutional Support and Guidance. These themes correspond to the five research questions addressing student behavior, motivations, social norms, ethical awareness, and institutional practices.

a) LLMs as Learning Substitutes

Consistent with the study's operational definition of over-reliance, students frequently described using LLMs to explain difficult academic content, generate summaries, and complete assignments. For some, LLMs acted as an extension of class learning; for others, they replaced core tasks like outlining, synthesizing, or even thinking through a problem. One participant shared, "I just paste the prompt, get a response, and tweak it. It saves me from thinking too much." Several participants explicitly described disengaging from independent thinking. One student noted, "I don't really analyze anymore—I just take what ChatGPT gives and adjust it." Another shared, "Earlier I used to struggle and learn, now I just copy the idea and move on."

b) Time Pressure and Efficiency Seeking

Students emphasized that the appeal of LLMs lies in their speed and ability to simplify workloads. Several noted using LLMs to meet deadlines or reduce the need for extensive reading. As one student said, "I don't have time to read all the materials. ChatGPT helps me write faster."

c) Normalization and Peer Influence

LLM usage appears normalized in student communities, with participants describing it as "what everyone is doing." Social influence shaped not only students' adoption of the tool but also the perception that non-use may result in academic disadvantage. "If you don't use it, you fall behind," one student noted.

d) Ethical Ambiguity and Misuse

Students expressed uncertainty about where the line lies between acceptable and unethical use. Some felt uneasy about copying from LLMs but did so anyway. Others believed minor editing made the content "original enough."

e) Lack of Institutional Support and Guidance

Students reported a lack of faculty guidance on how to use LLMs responsibly. None recalled any formal training or university policies on AI use. "Teachers don't even mention it," one student said.

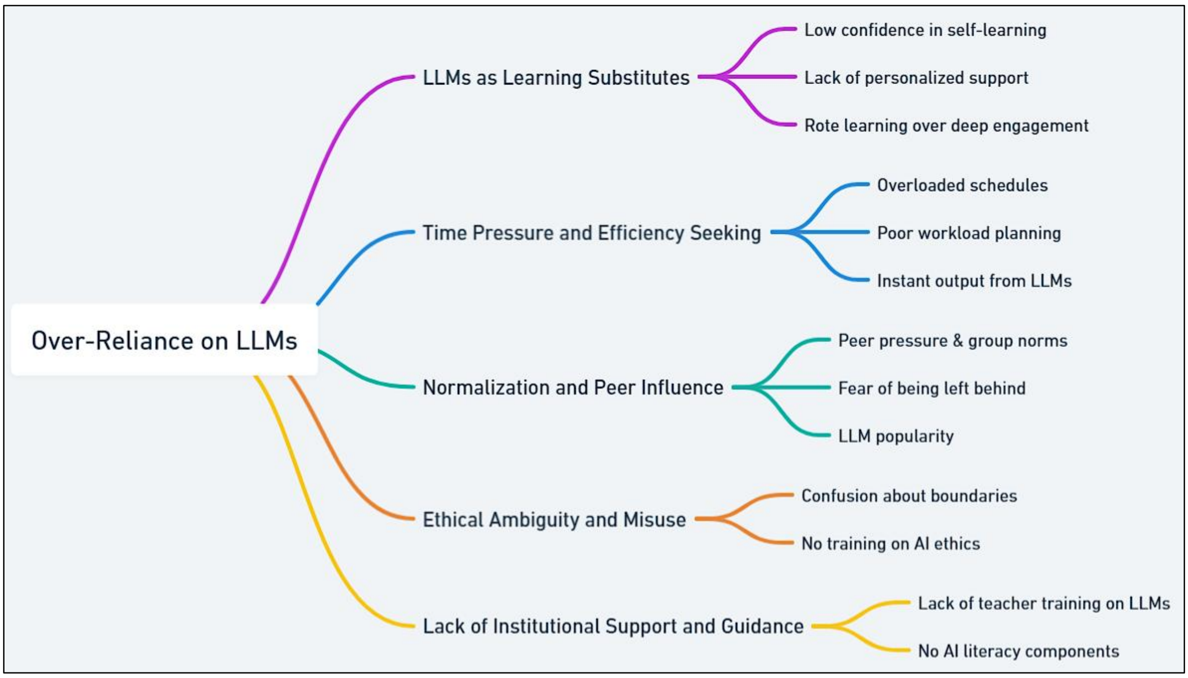

Figure 1: Root Causes of Over-Reliance on Large Language Models (LLMs) in Higher Education

As shown in Figure 1, The interconnectedness and cyclic reinforcement of the above themes and their root causes are visually represented in the Cyclical Fishbone Diagram. This diagram captures the systemic drivers behind students' over-reliance on Large Language Models (LLMs) such as ChatGPT, a Root Cause Analysis (RCA) was conducted and visually represented using a customized Fishbone Diagram. The RCA revealed five major thematic categories, each comprising interrelated factors across six domains commonly associated with educational systems: student factors, institutional/faculty practices, technological access and design, peer/social influence, curriculum and assessment design, and time/workload pressure.

Theme 1: LLMs as Learning Substitutes

A recurring pattern in the interviews was the use of LLMs as substitutes for deep learning. Many students described relying on LLMs for quick explanations, definitions, and task completions. The RCA revealed that this behavior stems from low confidence in self-learning, often reinforced by a lack of personalized support from faculty. Students cited challenges in understanding complex topics, which they felt were not adequately addressed in lectures. LLMs' design—providing simplified, instant responses—further reinforces this dependency. Furthermore, a curriculum that favors rote learning over critical engagement leaves little room for developing independent thinking, thus promoting the replacement of original cognitive effort with AI-generated output.

Theme 2: Time Pressure and Efficiency Seeking

Students frequently expressed that their academic workload and looming deadlines pushed them to use LLMs as time-saving tools. RCA revealed that overloaded schedules, tight academic calendars, and limited support for time management skills contributed to this reliance. LLMs, which offer immediate outputs and summaries, became essential to meeting multiple concurrent demands. However, this pattern reflects a structural imbalance in curriculum design that prioritizes content coverage over sustainable learning practices. The lack of time management training within courses was identified as a systemic gap that exacerbates students' inclination toward efficiency over reflection.

Theme 3: Normalization and Peer Influence

Social norms and peer behavior emerged as significant drivers of LLM use. Students often described LLM use as a normalized behavior—"everyone uses it"—pointing to a culture of implicit acceptance. RCA linked this normalization to peer pressure, fear of being left behind, and the absence of faculty intervention. Teachers often did not address LLM usage, either due to uncertainty about policies or passive attitudes. Institutional adaptation to LLMs has lagged, with most courses lacking explicit norms or guidelines around their acceptable use. Consequently, a silent consensus forms among students that using LLMs extensively is not only common but necessary to keep up academically. Notably, expressions of peer pressure and competition varied across disciplines. Engineering and Management students more frequently described performance-driven LLM use linked to grades and placement expectations, whereas Pharmacy and Law students emphasized conformity to peer practices and fear of academic disadvantage. Despite these variations, a shared perception emerged across institutions that LLM use was increasingly normalized and implicitly necessary for academic survival.

Theme 4: Ethical Ambiguity and Misuse

The ethical dimensions of LLM use were particularly ambiguous for many students. Several were unsure whether their use of ChatGPT constituted academic misconduct. RCA identified a lack of ethics training on AI tools as a core issue. Students noted that academic integrity policies had not evolved to reflect the realities of AI-assisted work. The design of LLMs—particularly their ease of copy-paste functionality—also contributes to behaviors that may blur the lines between assistance and plagiarism. The absence of digital literacy education and clearly defined expectations further fuels misuse, creating a zone of ethical ambiguity that many students struggle to navigate.

Theme 5: Lack of Institutional Support and Guidance

Across the board, students reported feeling unsupported in understanding how to use LLMs responsibly. RCA uncovered gaps in faculty knowledge and preparedness, with many educators admitting that they had received no formal training on the use or implications of generative AI. Institutions, likewise, had not fully integrated AI tools into teaching strategies or curricula. Without AI literacy components in course design or clear institutional frameworks, students are left to experiment with LLMs independently, often adopting habits that favor convenience over comprehension. This perceived lack of guidance creates a vacuum in which misuse, over-reliance, and confusion flourish.

Together, these five themes demonstrate that students' over-reliance on LLMs is not merely an issue of individual behavior but the result of a broader, cyclical system of pressures, gaps, and enablers. The Fishbone Diagram accompanying this analysis captures the complex interplay of student, technological, pedagogical, and institutional causes, highlighting the urgent need for coordinated interventions at multiple levels of the educational ecosystem.

Discussion

This discussion interprets the findings on students' over-reliance on Large Language Models (LLMs) in higher education, situating them within broader ethical, pedagogical, and institutional contexts. Drawing on the Root Cause Analysis (RCA) and literature, the analysis highlights how motivations such as time pressure, normalization through peer influence, and lack of institutional guidance converge to shape unsustainable learning behaviors. The implications are examined through the lens of inclusive and responsible AI integration.

The integration of Large Language Models (LLMs) into academic settings, while offering efficiency and personalized support, raises serious concerns regarding cognitive offloading and the erosion of critical thinking skills. As revealed in the Root Cause Analysis (RCA), many students substitute deep engagement with AI-generated content due to low self-confidence and an educational environment that prioritizes coverage over conceptual depth. This substitution process is driven by a desire for quick answers and is compounded by a lack of personalized academic support, ultimately leading students to adopt passive learning behaviors. Literature corroborates these findings, highlighting how overconfidence (52). The imitation of AI reasoning patterns diminishes students' capacity for independent analysis and problem-solving (27). Moreover, reliance on LLMs undermines critical engagement by encouraging students to accept content at face value without interrogation, thus impeding the development of analytical frameworks necessary for effective learning. These patterns pose a direct threat to responsible innovation in learning environments. Therefore, educational institutions must critically assess how LLMs are integrated and develop pedagogical strategies that foster reflective thinking, questioning, and intellectual autonomy to safeguard the future of transformative education. These patterns are grounded in students' self-reported behaviors and are further corroborated by RCA findings, which reveal how institutional workload pressures and limited pedagogical guidance reinforce surface-level engagement.

The findings reveal that institutional pressures, including overloaded academic schedules, dense curricula, and frequent deadlines, compel students to prioritize efficiency and task completion over deep, meaningful learning. As illustrated in the Root Cause Analysis (RCA), these structural constraints—coupled with limited institutional support for time management—drive students toward LLMs as a convenient means of producing academic outputs quickly. The absence of explicit time management training within curricula further exacerbates this dependency, reinforcing surface-level engagement with academic content. Literature confirms that such systemic inefficiencies lead to shallow learning habits and undermine students' capacity to develop autonomy and critical self-regulation (21, 53). These patterns not only reflect broader curricular challenges but also point to the need for institutional reforms that prioritize skill development alongside content mastery. Therefore, fostering effective educational practices demands integrative solutions—such as embedding time management, metacognitive training, and AI literacy into academic programs—to ensure that students are empowered to navigate academic demands without compromising the integrity of their learning.

The normalization of LLM use within academic environments is significantly shaped by peer influence and prevailing cultural norms, which collectively guide student behavior in subtle yet powerful ways. As highlighted in the Root Cause Analysis (RCA), students often perceive widespread LLM use as a peer-endorsed norm, fostering a culture where reliance on AI tools becomes silently accepted—if not expected. The absence of clear institutional guidelines and the lack of proactive faculty discourse further reinforce this normalization, leaving students to navigate ethical boundaries independently. Research on peer norms underscores how social dynamics in classrooms can both enable and constrain behavior, particularly when students conform to dominant practices for fear of exclusion or falling behind (33, 36). Moreover, classroom and institutional cultures that do not explicitly address responsible AI use inadvertently promote uncritical adoption. These insights reveal a critical need to recalibrate educational environments by fostering transparent discussions, modeling ethical AI use, and embedding peer-led digital literacy initiatives. By addressing the social dimensions of LLM usage, institutions can cultivate responsible innovation and peer cultures that support ethical engagement with emerging technologies. These findings suggest that peer pressure operates differently across institutional and disciplinary contexts but is consistently reinforced by competitive assessment structures and the absence of explicit institutional guidance on LLM use.

Students' confusion over the ethical boundaries of LLM use reflects a broader institutional failure to provide adequate ethics training and digital literacy, as underscored in the Root Cause Analysis (RCA). Participants in the study expressed uncertainty about what constitutes acceptable use of AI, particularly in academic writing and problem-solving tasks, revealing gaps in their understanding of academic integrity in the digital era. This ethical ambiguity is exacerbated by the absence of institutional frameworks that clarify responsible use, with many universities yet to implement standardized policies or integrate AI ethics into their curricula (26, 54). Without foundational training, students are left to make subjective decisions about LLM use, often resorting to practices that compromise their learning and academic honesty. The literature further emphasizes the need for theoretical grounding in Utilitarianism, Deontology, and Virtue Ethics to support critical discernment in AI-assisted learning (55). Moreover, the lack of institutional AI literacy programs and faculty guidance prevents students from developing the skills needed to interrogate bias, ensure transparency, and uphold digital responsibility. Clear institutional policies, ethics-infused pedagogy, and comprehensive AI literacy initiatives are essential to cultivating a culture of digital integrity and responsible innovation in education.

This study contributes to the educational technology literature by reframing student engagement with Large Language Models (LLMs) through a systemic rather than individualistic lens. Theoretically, it advances existing scholarship by introducing Root Cause Analysis (RCA) as both a conceptual and methodological framework for examining AI-related learning behaviors. Whereas much of the current literature emphasizes technology adoption, perceived usefulness, or learning outcomes, this study employs RCA to uncover the deeper cognitive, social, pedagogical, and institutional conditions that collectively shape student over-reliance on LLMs. In doing so, it moves beyond surface-level usage patterns to provide a multi-level explanation of AI dependency that situates individual motivations—such as efficiency seeking and academic pressure—within broader peer norms, curriculum structures, and institutional gaps in guidance. Empirically, the study offers original qualitative insights from professional undergraduate students across Engineering, Pharmacy, Management, and Law in the Indian higher education context, an underrepresented setting in current LLM research. By capturing cross-disciplinary narratives, the findings demonstrate how over-reliance emerges not merely from student choice but from interconnected academic systems that normalize cognitive offloading. Importantly, this research shifts the prevailing discourse from examining the isolated "impact" of AI tools toward conceptualizing AI dependency systems, thereby foregrounding institutional accountability, pedagogical design, and ethical literacy as central to responsible AI integration in higher education.

Despite the growing integration of AI tools like LLMs in higher education, findings from the study and Root Cause Analysis (RCA) reveal a significant gap in institutional and pedagogical readiness to guide their responsible use. Students frequently reported feeling unsupported, attributing their over-reliance on AI to a lack of faculty guidance, unclear academic policies, and limited exposure to ethical AI use frameworks. This vacuum of institutional clarity creates an environment where misuse flourishes and students navigate AI integration in isolation, often without the critical literacy required to evaluate outputs responsibly. As highlighted in the literature (54, 56, 57). Also the institutional policies remain uneven, and faculty often lack adequate training to embed AI tools meaningfully into pedagogy. The absence of AI literacy components within curricula, coupled with educators' limited understanding of LLM capabilities, undermines efforts to promote ethical and effective AI integration. Without proactive and inclusive institutional responses, the educational promise of AI risks reinforcing existing inequities and undermining the transformative potential of higher education. Therefore, preparing institutions and faculty through structured policies, ongoing training, and curriculum reform is essential to harness AI's potential responsibly and equitably.

To translate these findings into practice, this study proposes a phased implementation framework for responsible LLM integration. In the short term, institutions can adopt low-cost, high-feasibility measures such as faculty workshops on ethical AI use, incorporation of brief AI literacy modules within existing courses, and dissemination of interim guidelines clarifying acceptable LLM practices. Medium-term strategies include curriculum redesign to embed critical thinking and AI evaluation skills, development of assessment models that discourage AI substitution, and creation of faculty learning communities to support pedagogical adaptation. Long-term reforms require structural alignment at institutional and policy levels, including accreditation standards for AI ethics education, sustained professional development programs, and national frameworks guiding generative AI in higher education.

Feasibility is enhanced by leveraging existing institutional mechanisms such as teaching–learning centers, curriculum committees, and student support services, enabling incremental adoption without extensive new infrastructure. Prioritization should begin with pedagogical capacity-building and ethical literacy, as these interventions offer immediate impact while laying the foundation for broader structural change.

Conclusion

This study explored student over-reliance on Large Language Models (LLMs) in higher education, identifying five interrelated themes: learning substitution, time pressure and efficiency seeking, peer normalization, ethical ambiguity, and institutional gaps in guidance. Findings indicate that LLM engagement is not merely a technological trend but reflects deeper pedagogical, social, and structural dynamics shaped by academic pressure, limited AI literacy, and reduced critical reflection. In the absence of ethical scaffolding and instructional support, excessive reliance risks undermining educational quality and critical thinking. Addressing these challenges requires integrated institutional policies that promote responsible AI use, ethical literacy, and reflective learning practices, supported through curriculum integration, faculty development, and peer-informed norms.

The study contributes theoretically by reframing LLM over-reliance as a systemic phenomenon rather than an individual deficit, empirically by providing qualitative evidence from an underexplored professional education context, and practically by proposing a framework for responsible AI integration grounded in institutional accountability and pedagogical readiness. Effective responses require coordinated, staged interventions, beginning with AI literacy and faculty capacity-building, followed by assessment redesign and curriculum alignment, and ultimately reinforced through institutional and legislative frameworks. Such a phased approach enhances feasibility and sustainability while enabling higher education systems to harness LLM benefits without compromising critical thinking, equity, or academic integrity.

This study is limited by its qualitative design and sample size, which restrict broader institutional generalization, as well as by the rapidly evolving nature of AI technologies. Disciplinary variations and direct measures of critical thinking outcomes were beyond the scope of this research. Future studies should adopt longitudinal, mixed-method, and cross-institutional approaches to examine how LLM use evolves over time and influences cognitive development. Comparative and experimental designs would further clarify how institutional policies, peer norms, and instructional strategies shape ethical engagement with AI, supporting evidence-based models that foster critical learning while mitigating overdependence.

Abbreviations

None.

Acknowledgement

None.

Author Contributions

All authors have equally contributed.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

Data supporting the findings of this study are available upon request from the corresponding author.

Declaration of Artificial Intelligence (AI) Assistance

No generative AI tools were used in the conception, writing, or preparation of this paper.

Ethics Approval

Ethical clearance for this study was based on the provision of informed consent from all participants, ensuring their voluntary participation and understanding of the research's purpose and procedures.

Funding

This research received no external funding.

References

1. Anjali P, Sreerekha S. Navigating the artificial intelligence (AI) Revolution: The paradigm shift in higher education. Educational Administration: Theory and Practice. 2024;30(5):12742–5. https://doi.org/10.53555/kuey.v30i5.5301
2. Begum I. Role of artificial intelligence in higher education-an empirical investigation. International Research Journal on Advanced Engineering and Management (IRJAEM). 2024;2(03):49–53. https://doi.org/10.47392/IRJAEM.2024.0009
3. Kamalov F, Gurrib I. A new era of artificial intelligence in education. Sustainability. 2023;15(16):12451. https://doi.org/10.3390/su151612451
4. Deri MN, Singh A, Zaazie P, *et al*. Leveraging artificial intelligence in higher educational institutions: A comprehensive overview. Revista de Educación y Derecho. 2024;(30):45777. https://doi.org/10.1344/REYD2024.30.45777
5. Kayyali M. AI in Higher Education: Revolutionizing Curriculum and Administration. In: AI Adoption and Diffusion in Education. IGI Global Scientific Publishi ng. 2025:31–62. https://doi.org/10.4018/979-8-3693-7949-3.ch002
6. Al Samman AM. Harnessing potential: Meta-analysis of AI integration in higher education. Proceedings of the 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS); Manama, Bahrain. IEEE. 2024:1-7. https://doi.org/10.1109/ICETSIS61505.2024.10459420
7. Khatri BB, Karki PD. Artificial intelligence (AI) in higher education: Growing academic integrity and ethical concerns. Nepalese Journal of Development and Rural Studies. 2023;20(1):1–7. https://doi.org/10.3126/njdrs.v20i01.64134
8. Matochová J, Kowaliková P. Transforming higher education: Psychological and sociological perspective (the use of artificial intelligence). R&E-SOURCE. 2024;176–81. https://doi.org/10.53349/resource.2024.is1.a1253
9. Eden CA, Chisom ON, Adeniyi IS. Integrating AI in education: Opportunities, challenges, and ethical considerations. Magna Scientia Advanced Research and Reviews. 2024;10(2):6–13. https://doi.org/10.30574/msarr.2024.10.2.0039
10. Farahani MS, Ghasmi G. Artificial intelligence in education: A comprehensive study. 2024:1379. https://doi.org/10.59400/fes.v2i3.1379
11. Dicheva D, Dichev C, Agre G, *et al*. Gamification in education: A systematic mapping study. Educational Technology & Society. 2015;18(3):75-88. https://www.jstor.org/stable/jeductechsoci.18.3.75
12. Sasipriya A, Reddy K. AI in Education: A neutrosophic graph framework for evaluating challenges and opportunities. IEEE. 2024:1–6. https://doi.org/10.1109/IDICAIEI61867.2024.10842902
13. Kaiser G, Kaiser S. AI in education: Reflections and future directions for pedagogical and andragogical integration. Integrating AI Into Pedagogical Education. IGI Global Scientific Publishing. 2025:241–60. https://doi.org/10.4018/979-8-3373-0502-8.ch012
14. Gerver E, Gerver E. Promises and pitfalls. Humanizing Technology: Computers in Community Use and Adult Education. 1986;155–63. https://doi.org/10.1007/978-1-4615-9448-2_7
15. Hannan A, Silver H, English S. Teaching and learning in higher education: Issues of innovation. Differing visions of a Learning Society. Policy Press. 2000:143–70. https://doi.org/10.46692/9781847425195.005
16. Durso F, Raunak M, Kuhn R, *et al*. Analyzing failures in artificial intelligent learning systems (FAILS). IEEE. 2022:7–8. https://doi.org/10.1109/STC55697.2022.00010
17. Pan R, Zhang Z, Li X, *et al*. Unsupervised root-cause analysis for integrated systems. IEEE. 2020:1–10. doi: 10.1109/ITC44778.2020.9325268
18. Wangdi P. Integrating artificial intelligence in education: Trends and opportunities. International Journal of Research in STEM Education. 2024;6(2):50-60. https://doi.org/10.33830/ijrse.v6i2.1722
19. Naveen KHN, Mahadevaswamy, Praveena KS, *et al*. Impact of AI on education and the need for academia to adopt: A review. Journal of Engineering Education Transformations. 2024;37(Special Issue 2):865-72. eISSN: 2394-1707
20. Gerlich M. AI tools in society: Impacts on cognitive offloading and the future of critical thinking. Societies. 2025;15(1):6. https://doi.org/10.3390/soc15010006
21. Jungherr A. Using ChatGPT and other large language model (LLM) applications for academic paper assignments. SocArXiv [Preprint]. 2023. https://doi.org/10.31235/osf.io/d84q6
22. Sohail A, Zhang L. Using large language models to facilitate academic work in the psychological sciences. Current Psychology. 2025:7910–8. https://doi.org/10.1007/s12144-025-07438-2
23. Raihan N, Siddiq ML, Santos JC, *et al*. Large language models in computer science education: A systematic

literature review. Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 2025:938-44. https://doi.org/10.1145/3641554.3701863
24. Wangwiwattana C, Tongvivat Y. Automating academic assessment: A large language model approach. 7th International Conference on Information Technology; Chiang Rai, Thailand. IEEE. 2023:330-4. https://doi.org/10.1109/InCIT60207.2023.10412991
25. Dong B, Bai J, Xu T, *et al*. Large language models in education: A systematic review. In IEEE. 2024:131–4. https://doi.org/10.1109/CSTE62025.2024.00031
26. Yan L, Sha L, Zhao L, *et al*. Practical and ethical challenges of large language models in education: A systematic scoping review. British Journal of Educational Technology. 2024;55(1):90–112. https://doi.org/10.1111/bjet.13370
27. Stuchlikova L, Weis M. From Information to insight: Reimagining critical thinking pedagogy in the age of artificial intelligence. IEEE. 2024:591–8. https://doi.org/10.1109/ICETA63795.2024.10850787
28. Chirayath G, Premamalini K, Joseph J. Cognitive offloading or cognitive overload? How AI alters the mental architecture of coping. Frontiers in Psychology. 2025;16:1699320. https://doi.org/10.3389/fpsyg.2025.1699320
29. Gonsalves C. Generative AI's impact on critical thinking: Revisiting Bloom's Taxonomy. Journal of Marketing Education. 2024:1-16. https://doi.org/10.1177/02734753241305980
30. Moustaghfir S, Brigui H. Navigating critical thinking in the digital era: An informative exploration. International Journal of Linguistics, Literature and Translation. 2024;7(1):137–43. https://doi.org/10.32996/ijllt.2024.7.1.11x
31. Chaparro-Banegas N, Mas-Tur A, Roig-Tierno N. Challenging critical thinking in education: new paradigms of artificial intelligence. Cogent Education. 2024;11(1):2437899. https://doi.org/10.1080/2331186X.2024.2437899
32. Kenedy RA. The challenges of critical thinking in the era of artificial intelligence. European Journal of Multidisciplinary Studies. 2024;9(2):19–36. https://doi.org/10.26417/hfdngd20
33. McKeown S, Taylor LK. Perceived peer and school norm effects on youth antisocial and prosocial behaviours through intergroup contact in Northern Ireland. British Journal of Social Psychology. 2018;57(3):652–65. doi: 10.1111/bjso.12257
34. Franklin-Gillette S, DuPaul GJ, Fu Q, *et al*. Peer Influence in a school for youth with emotional and behavioral disorders. Journal of Emotional and Behavioral Disorders. 2023;31(1):3–13. http://dx.doi.org/10.1177/10634266221076471
35. Morrongiello BA, McArthur BA, Kane A, *et al*. Only kids who are fools would do that!: Peer social norms influence children's risk-taking decisions. Journal of Pediatric Psychology. 2013;38(7):744–55. doi: 10.1093/jpepsy/jst019
36. Laninga-Wijnen L, Harakeh Z, Dijkstra JK, *et al*. Aggressive and prosocial peer norms: Change, stability, and associations with adolescent aggressive and prosocial behavior development. The Journal of Early Adolescence. 2018;38(2):178–203. https://doi.org/10.1177/0272431616665211
37. Pavin Ivanec T, Čorkalo Biruški D, Pehar L. Effects of intergroup contact norms and school climate on youth self-reported outgroup prosocial behaviour in school. Current psychology. 2023;42(9):7284–96. doi: 10.1007/s12144-021-01714-7
38. Laninga-Wijnen L, Harakeh Z, Dijkstra JK, *et al*. Aggressive and prosocial peer norms: Change, stability, and associations with adolescent aggressive and prosocial behavior development. The Journal of Early Adolescence. 2018;38(2):178–203. doi: 10.1177/0272431616665211
39. Shin H. Examining early adolescents' peer climate using descriptive and status norms on academic engagement and aggressive behavior in the classroom. Asia Pacific Education Review. 2017;18:309–20. https://doi.org/10.1007/s12564-017-9494-5
40. Pinho A da S, Molleman L, Braams BR, *et al*. Majority and popularity effects on norm formation in adolescence. Scientific Reports. 2021;11(1):12884. https://doi.org/10.1038/s41598-021-92482-8
41. Qin H. Transforming education with large language models: Opportunities, challenges, and ethical considerations. 2026;5(1):177. doi: 10.13140/RG.2.2.16976.52488
42. Farhi F, Jeljeli R, Aburezeq I, *et al*. Analyzing students' views, concerns, and perceived ethics about ChatGPT usage. Computers and Education: Artificial Intelligence. 2023;5:100180. https://doi.org/10.1016/j.caeai.2023.100180
43. Razafinirina MA, Dimbisoa WG, Mahatody T. Pedagogical alignment of large language models (LLM) for personalized learning: A survey, trends and challenges. Journal of Intelligent Learning Systems and Applications. 2024;16(4):448–80. doi: 10.4236/jilsa.2024.164023
44. Percarpio KB, Watts BV, Weeks WB. The effectiveness of root cause analysis: what does the literature tell us? The Joint Commission Journal on Quality and Patient Safety. 2008;34(7):391–8. doi: 10.1016/s1553-7250(08)34049-5
45. Kulangara KJ. Designing and building a platform for teaching introductory programming supported by large language models [master's thesis]. Espoo (Finland): Aalto University, School of Science; 2023. https://aaltodoc.aalto.fi/server/api/core/bitstreams/2eae5618-109d-43b9-9c74-38119cf3e593/content
46. Wong A, Wentz E, Palisano N, *et al*. Role of artificial intelligence in pharmacy practice: a narrative review. Journal of the American College of Clinical Pharmacy. 2023;6(11):1237–50. https://doi.org/10.1002/jac5.1856
47. Siino M, Falco M, Croce D, *et al*. Exploring LLMs applications in law: A literature review on current legal NLP approaches. IEEE Access. 2025. doi: 10.1109/ACCESS.2025.3533217
48. Rane N, Shirke S, Choudhary SP, *et al*. Artificial intelligence in education: A SWOT analysis of ChatGPT and its impact on academic integrity and research. Journal of ELT Studies. 2024;1(1):16–35. doi: 10.48185/jes.v1i1.1315

49. Braun V, Clarke V. Using thematic analysis in psychology. Qualitative Research in Psychology. 2006;3(2):77–101. doi: 10.1191/1478088706qp063oa
50. Shukla SK, Sushil, Sharma MK. Managerial paradox toward flexibility: Emergent views using thematic analysis of literature. Global Journal of Flexible Systems Management. 2019;20(4):349–70. doi: 10.1007/s40171-019-00220-x
51. Castleberry A, Nolen A. Thematic analysis of qualitative research data: Is it as easy as it sounds? Currents in pharmacy teaching and learning. 2018;10(6):807–15. doi: 10.1016/j.cptl.2018.03.019
52. Jerrim J, Parker PD, Shure N. Overclaiming. An international investigation using PISA data. Assessment in Education: Principles, Policy & Practice. 2023;30(5–6):351–71. doi: 10.1080/0969594X.2023.2238248
53. Zhai C, Wibowo S, Li LD. The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. Smart Learning Environments. 2024;11(1):28. doi: 10.1186/s40561-024-00316-7
54. Peñalvo FJG, Alier M, Pereira J, *et al*. Safe, transparent, and ethical artificial intelligence: Keys to quality sustainable education (SDG4). IJERI: International Journal of Educational Research and Innovation. 2024;(22):1–21. doi: 10.46661/ijeri.11036
55. Sumbera BG. The ethical use of AI in education. Integrating AI Into Pedagogical Education. IGI Global Scientific Publishing. 2025:175–210. doi: 10.4018/979-8-3693-6130-6.ch008
56. Al Zaidy A. The impact of generative AI on student engagement and ethics in higher education. Journal of Information Technology, Cybersecurity, and Artificial Intelligence. 2024;1(1):30–8. https://doi.org/10.70715/jitcai.2024.v1.i1.004
57. Paschal MJ, Melly IK. Ethical guidelines on the use of AI in education. Creative AI tools and ethical implications in teaching and learning. IGI Global. 2023:230–45. doi: 10.4018/979-8-3693-0205-7.ch013

How to Cite: Pachava V, Lasekan OA, Pena MTG, Swaroop KR, Guniganti S. Over-reliance on Large Language Models in Higher Education: Ethical and Institutional Challenges in Responsible AI Integration. Int Res J Multidiscip Scope. 2026; 7(2): 213-226. DOI: 10.47857/irjms.2026.v07i02.09619