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Research Article

Impact of Large Language Models on Personalized Learning, Assessment Automation, and Student Outcomes in Higher Learning Institution

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Abstract
This study investigated the multifaceted influence of Large Language Models (LLMs) on teaching and learning within a private higher education institution in Rwanda during the 2024–2025 academic year. A total of 658 students and 28 lecturers participated, providing a comprehensive perspective on both user experiences and professional concerns. Using a quantitative approach, the study employed Multivariate Analysis of Variance (MANOVA) to examine how the use of LLMs relates to students' perceptions of personalized learning effectiveness, academic performance improvement, online engagement, satisfaction with assessment feedback, and motivation for lifelong learning. Findings from the student indicated that LLMs are widely perceived as beneficial across multiple dimensions of the learning process. Students reported that LLMs enhance personalized learning by providing adaptive guidance, improving academic performance through instant clarification and practice support, and increasing online engagement by offering interactive and accessible learning assistance. The results further showed that LLMs contribute to greater satisfaction with feedback mechanisms and stimulate motivation for continuous and self-directed learning. These statistically significant associations point to the strong potential of LLMs to enrich higher education outcomes. In contrast, the lecturers' data revealed notable concerns related to data privacy, ethical use, and algorithmic bias. Lecturers expressed significant apprehension regarding students' overreliance on LLMs, the risks associated with inaccurate or biased outputs, and the potential erosion of academic integrity. Their perceptions underscore the need for safeguards that ensure responsible and ethical use of AI in academic settings. Overall, the findings highlighted a dual reality: while LLMs hold transformative potential for improving learning experiences, their integration must be supported by robust institutional policies, targeted capacity-building initiatives, and ongoing research. Such measures are essential to promote equitable, ethical, and effective adoption of LLMs in higher education.

Keywords: Large Language Models, Higher Education, Personalized Learning, Ethical Concerns

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1. INTRODUCTION

The rapid evolution of artificial intelligence, particularly in the domain of Large Language Models (LLMs) such as ChatGPT, has instigated a transformative shift across various sectors, with education being a prominent beneficiary (Chaitanya & Rolla, 2024). These advanced AI tools possess the capacity to revolutionize traditional learning paradigms by offering personalized learning experiences, enhancing engagement, and streamlining administrative tasks like assessment (Zohuri & Mossavar-Rahmani, 2024). As higher learning institution worldwide explore the integration of LLMs into their pedagogical frameworks, understanding the multifaceted impact of these technologies on both students and lecturers becomes paramount. This study investigated the perceptions and experiences of students and lecturers within a Rwandan private higher learning institution, aiming to shed light on the real-world implications of LLM adoption in the academic landscape.

The integration of LLMs in higher education presents both immense opportunities and significant challenges (Alotaibi, 2024). While the potential for improved academic performance through personalized learning systems, increased student engagement in online environments, and enhanced satisfaction with assessment feedback is widely recognized, crucial considerations surrounding data privacy, ethical use, and algorithmic bias also emerge (Bhatia et al., 2024). Addressing these concerns was vital for the responsible and effective deployment of LLMs, ensuring equitable access and raising an environment of trust. This research systematically investigated these key areas, providing empirical evidence to inform best practices and policy development for the thoughtful incorporation of LLMs in academic settings.

This study, conducted during the 2024-2025 academic year at a private higher learning institution in Rwanda, involved a varied sample of 686 participants, including 658 students and 28 lecturers. Utilizing a strong methodology centered on Multivariate Analysis of Variance (MANOVA), the research explored the relationships between LLM usage and exposure (independent variables) and outcomes such as perceived effectiveness, academic engagement, and satisfaction with assessment processes, ethical concerns, and motivation for lifelong learning (dependent variables). The findings derived from this comprehensive demographic representation offer valuable insights into the dynamic interplay between LLMs and various facets of the higher education experience in a contemporary African context.

Therefore, this study aims to address the following research questions:

1. To what extent do students in higher learning institution perceive LLM-enhanced personalized learning systems as effective in improving their academic performance?
2. What is the relationship between the frequency of LLM usage (e.g., ChatGPT) and students' engagement levels in online learning environments?
3. How significantly does the integration of LLMs in assessment and grading processes influence students' satisfaction with feedback quality and turnaround time?
4. To what extent do higher learning lecturers report concerns related to data privacy, ethical use, and bias when using LLMs in teaching and learning?
5. What is the statistical relationship between students' exposure to LLM-driven intelligent tutoring systems and their self-reported motivation for lifelong learning and skills development?

2. LITERATURE REVIEW

The rapid advancement of artificial intelligence (AI), particularly Large Language Models (LLMs), has profoundly influenced various sectors, with education emerging as a significant area of impact (Jelodar, 2025). The potential of LLMs to revolutionize pedagogical practices, from personalized learning to automated assessment, has garnered considerable attention from researchers and educators alike (Shahzad et al., 2025). This review aimed to synthesize existing research on the integration of LLMs in higher education, focusing on their perceived effectiveness in improving academic performance, their relationship with student engagement, their influence on assessment and feedback, the concerns of educators regarding their ethical deployment, and their role in fostering lifelong learning.

The concept of personalized learning, adjusting educational experiences to individual student needs, has long been a goal in education (Ahmed et al., 2025). Traditional approaches have often relied on adaptive learning technologies that use rule-based systems or student models to adjust content and pace (Qiang, 2025). The advent of LLMs, however, introduces a new paradigm for personalization (Zhu et al., 2025). Their ability to understand natural language queries, generate human-like text, and synthesize vast amounts of information allows for dynamic and highly customized learning pathways (Sharma et al., 2025). This capability extends beyond simple adaptive quizzes to providing on-demand explanations, creating varied practice problems, and offering truly individualized feedback, potentially addressing the different learning styles and paces of students in a way previously unattainable (Troussas et al., 2025).

Early research on AI in education highlighted the promise of intelligent tutoring systems (ITS) in providing individualized instruction (Ateş, 2025; Singh et al., 2025). These systems demonstrated effectiveness in improving student learning outcomes by adapting to individual performance and providing targeted support (Gomes, 2025). LLMs represent a significant leap forward in ITS capabilities, offering more sophisticated conversational interfaces and the ability to generate a wider range of explanations and examples (Casheekar et al., 2024). The intuitive interaction with LLMs simulators human-to-human tutoring more closely, which could enhance student engagement and understanding, thereby leading to improved academic performance as perceived in the present study.

However, the efficacy of personalized learning, even with advanced AI, links on its effective implementation (Alonso et al., 2025). Simply introducing an LLM does not guarantee improved outcomes; rather, it requires thoughtful integration into the curriculum and pedagogical design (Sharma et al., 2025). While studies like Velmurugan et al. (2025) have indeed shown that personalized learning approaches, in general, lead to improved academic achievement and student satisfaction, the unique contribution of LLMs in driving this personalization warrants specific investigation. The current study's findings, indicating a strong positive perception of LLM-enhanced personalized learning, reinforce this evolving understanding and suggest that the advanced natural language capabilities of LLMs are a key differentiator.

Student engagement is a critical factor in online learning environments, influencing learning outcomes and retention (Faro et al., 2025). Digital tools and interactive technologies have long been recognized for their potential to enhance student participation (Han et al., 2025). The emergence of LLMs offers novel avenues for raising engagement, from providing instant answers and clarifications to facilitating interactive discussions and creative content generation (Sharma et al., 2025). The accessibility and responsiveness of LLMs can reduce feelings of isolation in online settings and provide immediate intellectual stimulation, thereby potentially increasing behavioral, cognitive, and emotional engagement (Zheng et al., 2025).

Research on technology-enhanced learning consistently points to increased engagement when students are provided with dynamic and accessible resources. LLMs, such as ChatGPT, fit this description by offering readily available support for various learning tasks (Indumathy & Mujra, 2025). Students use LLMs to explore complex topics, generate ideas, or even simulate dialogues for practice, all of which contribute to active participation in their learning journey (Nelson et al., 2025). This direct and often personalized interaction has significantly elevated a student's sense of agency and involvement in online learning.

However, the nature and depth of engagement with LLMs remain a subject of ongoing debate (Hayes, 2025; Zhang et al., 2025). While LLMs can provide quick information, the extent to which this translates into deeper cognitive processing and sustained emotional investment is not always clear (Ratican & Hutson, 2024). Some scholars caution that passive consumption of LLM-generated content might lead to superficial learning rather than genuine engagement (Pozdniakov et al., 2025). The present study's finding of a statistically significant but modest effect size for LLM usage frequency on student engagement reflects this reality, suggesting that while LLMs can contribute to engagement, they are not a remedy and their impact might be incremental, requiring deliberate pedagogical strategies to maximize their benefit.

Assessment and feedback are integral components of the learning process, profoundly influencing student learning and satisfaction (Levy-Feldman, 2025). Traditional assessment methods, particularly in large classes, often struggle with providing timely, personalized, and high-quality feedback (Gao, 2025). Automated feedback systems, utilizing natural language processing (NLP), have been explored as a solution to these challenges, showing improvements in feedback timeliness and, in many cases, perceived quality (Fisher et al., 2025). LLMs represent a powerful evolution in this domain, capable of generating more sophisticated, contextualized, and human-like feedback than previous NLP tools (Guizani et al., 2025).

The integration of LLMs into assessment processes can significantly enhance efficiency and effectiveness (Ogalo & Mtenzi, 2025). LLMs can assist in generating nuanced rubrics, providing instant feedback on written assignments, identifying common misconceptions, and even personalizing remedial suggestions (Okafor, 2025). The speed at which LLMs can process and return feedback addresses a critical student need, as timely feedback is crucial for formative learning and subsequent improvement (Lindsay et al., 2025). This efficiency alone can contribute substantially to student satisfaction with assessment processes.

Nevertheless, the quality and fairness of LLM-generated feedback remain a focal point of scholarly discussion (Jacobsen & Weber, 2025). Concerns about algorithmic bias, the potential for LLMs to miss subtle errors, or to provide overly generic feedback without a deep understanding of the student's context have been raised (Aperstein et al., 2025). While LLMs simulate human-like feedback, the underlying logic may not always be transparent, leading to questions about the perceived accuracy and trustworthiness of the feedback (Zhou et al., 2025). The present study's findings, indicating increased student satisfaction with feedback quality and turnaround time due to LLM integration, suggest a positive perception of these aspects, yet future research should delve deeper into the students' perception of accuracy and fairness.

The widespread adoption of LLMs in education also brings forth a spectrum of ethical considerations that are of paramount concern to educators (Yan et al., 2024). Issues related to data privacy, algorithmic bias, and responsible use are frequently discussed in the broader discourse on AI (Dong & Guo, 2025). In an educational context, these concerns are amplified, as student data is often sensitive, and the potential for biased algorithms to perpetuate educational inequities is a serious risk (Leong & Zhang, 2025). Lecturers, as frontline educators and guardians of academic integrity, are uniquely positioned to articulate these apprehensions (Onderi, 2025).

Data privacy is a significant concern, as LLMs require access to vast datasets for training and operation, which may include student interactions, assignments, and personal information (Das, Amini, & Wu, 2025). Lecturers worry about how this data is collected, stored, and utilized, and whether it adequately protects student anonymity and privacy rights (Plemons & Spiros, 2025). The ethical use of LLMs extends to issues of academic honesty, as students may be tempted to use these tools to generate assignments rather than demonstrating their own understanding, raising questions about plagiarism and the authenticity of student work (Leaton Gray et al., 2025).

Furthermore, the inherent biases present in the training data of LLMs can lead to algorithmic bias in their outputs, potentially affecting the fairness of assessment, the diversity of information provided, or even perpetuating stereotypes (Agarwal et al., 2025). This can lead to inequitable learning experiences for students from marginalized groups (Radu et al., 2025). The present study's finding of a highly significant extent of concern among lecturers regarding data privacy, ethical use, and algorithmic bias corroborates the existing literature and underscores the urgent need for strong institutional policies, ethical guidelines, and comprehensive training to mitigate these risks and ensure the responsible integration of LLMs in higher education.

In a rapidly changing world, raising lifelong learning and continuous skills development is more critical than ever (Ahsan, 2025). Intelligent tutoring systems (ITS), even before the advent of LLMs, have shown promise in promoting self-regulated learning and learner autonomy, encouraging students to take ownership of their educational journey (Mohebbi, 2025). LLM-driven intelligent tutoring systems, with their enhanced conversational and adaptive capabilities, hold even greater potential to cultivate these crucial dispositions for continuous learning (Rogers et al., 2025).

LLMs provide personalized and adaptive learning pathways that respond to individual learning styles and paces, raising a sense of mastery and encouraging exploration beyond formal curricula (Sharma et al., 2025). By offering on-demand support, personalized explanations, and diverse learning resources, LLM-driven systems can empower students to direct their own learning, a cornerstone of lifelong learning (Mounika et al., 2025). The ability of LLMs to generate various content and answer complex questions can also stimulate intellectual curiosity and a desire for deeper understanding, thereby motivating students to engage in continuous self-improvement and skills acquisition (George et al., 2025).

However, it is important to acknowledge that technology, while a powerful enabler, does not solely drive motivation for lifelong learning (Velmurugan et al., 2025). Intrinsic motivation, pedagogical strategies that encourage active learning, and a supportive educational environment all play critical roles (Ruziyevna, 2025). While LLM-driven tutoring systems can provide valuable tools and resources, they are likely to function as facilitators and enhancers rather than singular determinants of this complex motivational outcome (Cai et al., 2025; Sharma et al., 2025). The present study's finding of a statistically significant but moderate effect size for LLM-driven intelligent tutoring systems on self-reported motivation for lifelong learning and skills development aligns with this balanced perspective, suggesting a promising yet nuanced role for these technologies in fostering continuous learning.

3. METHODS

3.1. Design

This study employed a quantitative research design to investigate the impact of Large Language Models (LLMs) in higher education within a private higher learning institution in Rwanda during the 2024-2025 academic year. A cross-sectional survey approach was utilized to collect data from a variety of samples of students and lecturers, allowing for the examination of relationships between LLM use and various academic and pedagogical outcomes. The quantitative approach was selected to facilitate the systematic collection and statistical analysis of data, enabling the identification of patterns, relationships, and the generalizability of findings within the study population.

3.2. Participants

The study involved a total sample of 686 participants, comprising 658 students enrolled in the holiday session and 28 lecturers. Participants were drawn from a private higher learning institution in Rwanda during the 2024-2025 academic year. A convenience sampling method was employed to recruit participants who were readily accessible and willing to participate. All participation was strictly voluntary, and a detailed informed consent process was undertaken where all respondents were fully informed about the purpose and ethical considerations of the study prior to data collection. The student participants represented various academic programs and levels of study, ensuring a broad representation of the student body. Lecturers were drawn from different departments of education and possessed varying years of teaching experience, contributing to a comprehensive understanding of their perspectives. This different demographic composition was crucial for providing a comprehensive perspective on the impact of Large Language Models (LLMs) in higher education.

3.3. Instruments

Data were collected through structured questionnaires designed to gather information on key variables related to LLM usage and its impact. The questionnaires comprised sections designed to assess both independent and dependent variables. Independent variables included the frequency of LLM use and exposure to various LLM features. Dependent variables encompassed several constructs, specifically: perceived effectiveness of LLM-enhanced personalized learning on academic performance (measured by self-reported academic performance improvement and perceived personalized learning effectiveness), student engagement levels (measured by behavioral, cognitive, and emotional engagement scores), student satisfaction with assessment processes (measured by satisfaction with feedback quality and turnaround time), ethical concerns among lecturers (measured by level of concern about data privacy, ethical use, and algorithmic bias), and motivation for lifelong learning (measured by self-reported motivation for lifelong learning and self-reported skills development interest). The use of self-reported measures allowed for direct insights into participants' experiences and perceptions regarding LLM integration in their academic environment.

3.4. Data Analysis

The collected quantitative data were analyzed using Multivariate Analysis of Variance (MANOVA). MANOVA was chosen as the primary statistical technique due to its ability to simultaneously analyze the relationships between multiple independent variables and multiple dependent variables. This was particularly relevant given the study's focus on several outcome measures associated with LLM use. For each research question, MANOVA tests were conducted, and the results of various multivariate statistics, Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root were reported. These statistics provide different perspectives on the overall effect of the independent variables on the combined dependent variables. A significance level of $p < 0.05$ was adopted for all statistical tests. Partial Eta Squared (η_p^2) was reported as a measure of effect size, indicating the proportion of variance in the dependent variables that is explained by the independent variables. All statistical analyses were performed using appropriate statistical software.

3. RESULTS

3.1. Demographic Information

The study involved a total sample of 686 participants, comprising 658 students enrolled in the holiday session and 28 lecturers, all from a private higher learning institution in Rwanda during the 2024–2025 academic year. Participation was voluntary, and all respondents were fully informed about the purpose and objectives of the study prior to data collection. The student participants represented various academic programs and levels of study, while the lecturers were drawn from diverse faculties with varying years of teaching experience. This various demographic composition provided a comprehensive perspective on the impact of Large Language Models (LLMs) in higher education. The data collected focused on key variables such as frequency of LLM use and exposure to LLM features (independent variables), and outcomes such as perceived effectiveness, academic engagement, and satisfaction with assessment processes, ethical concerns, and motivation for lifelong learning (dependent variables). Multivariate Analysis of Variance (MANOVA) was employed to analyze the relationships among these variables.

Research Question 1: To what extent do students in higher learning institution perceive LLM-enhanced personalized learning systems as effective in improving their academic performance?

Table 1. Perceived Effectiveness of LLM-Enhanced Personalized Learning on Academic Performance

Multivariate Tests	Value	F	Hypothesis df	Error df	p-value	Partial Eta Squared
Pillai's Trace	0.345	25.12	3	654	< .001	0.103
Wilks' Lambda	0.655	25.11	3	654	< .001	0.103
Hotelling's Trace	0.529	25.15	3	654	< .001	0.103
Roy's Largest Root	0.380	41.04	3	654	< .001	0.159

The multivariate tests for Research Question 1, as presented in Table 1, strongly indicate that students in higher learning institution perceive LLM-enhanced personalized learning systems as significantly effective in improving their academic performance. All four multivariate statistics (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root) yielded highly significant p-values (<.001), suggesting a statistically robust relationship between the independent variables (LLM-enhanced personalized learning) and the dependent variables (self-reported academic performance improvement and perceived personalized learning effectiveness). The consistent significance across these tests underscores the reliability of this finding.

The Partial Eta Squared values, ranging from 0.103 to 0.159, indicate a moderate to large effect size. Specifically, the Pillai's Trace, Wilks' Lambda, and Hotelling's Trace show a Partial Eta Squared of 0.103, suggesting that approximately 10.3% of the variance in the combined dependent variables is attributed to the LLM-enhanced personalized learning systems. Roy's Largest Root, with a Partial Eta Squared of 0.159, highlights an even stronger effect on at least one linear combination of the dependent variables. These effect sizes are meaningful in educational research, suggesting that the integration of LLMs for personalized learning is not just statistically significant but also practically relevant in influencing student perceptions of academic improvement.

The significant F-values across all tests (ranging from 25.11 to 41.04) further strengthen the notion that there are significant differences in students' perceptions based on their exposure to LLM-enhanced personalized learning. The large Hypothesis df of 3 and Error df of 654 indicate a substantial sample size for student participants, contributing to the statistical power of these findings. This comprehensive analysis suggests that LLM-enhanced personalized learning is perceived by students as a valuable tool for enhancing their academic outcomes, likely due to its ability to tailor content, pace, and feedback to individual learning needs.

This positive perception might stem from several aspects of personalized learning systems powered by LLMs. For instance, these systems provide on-demand explanations, adaptive quizzes, and personalized recommendations, which directly contribute to students feeling more supported and understanding complex topics better. The self-reported nature of the dependent variables suggests that students themselves are noticing a tangible benefit to their learning processes and academic results when interacting with such systems.

The consistency of the p-values across all multivariate tests further validates the strong impact of LLM-enhanced personalized learning on students' perceived academic improvement. This suggests that the benefits are not isolated to a single aspect of personalized learning but rather a holistic enhancement across various dimensions, including how students gauge their own progress and the overall effectiveness of the learning process.

Therefore, the findings for Research Question 1 provide compelling evidence that LLM-enhanced personalized learning systems are perceived by students as a highly effective tool for improving academic performance. The statistically significant results and moderate to large effect sizes indicate that these systems hold considerable promise in optimizing learning experiences within higher education institutions.

The strong positive perception of LLM-enhanced personalized learning systems aligns with a growing body of literature highlighting the benefits of adaptive learning technologies. The study by Bhatia et al. (2024) has demonstrated that personalized learning approaches lead to improved academic achievement and student satisfaction. This study specifically contributes by focusing on the role of Large Language Models in driving this personalization, which is a relatively newer application compared to traditional adaptive learning algorithms. The current input from this study supports the notion that LLMs can indeed be a powerful engine for delivering highly individualized learning experiences, thereby reinforcing and expanding existing knowledge on the efficacy of personalized learning (Sharma et al., 2025).

However, a point of contrast might lie in the potential over-reliance or uncritical acceptance of LLM-driven personalization without considering potential biases and limitations inherent in the models (Alotaibi, 2024). While the results indicate positive perceptions, existing literature on AI in education often cautions against the black box nature of some AI systems and the need for explainable AI (Velmurugan et al., 2025). This study's current input, while positive, prompts further research into how these perceived benefits are achieved and if students are aware of the underlying mechanisms or potential pitfalls. It also provides a contemporary data point from a Rwandan context, adding geographical diversity to the discourse, as much of the existing literature originates from Western educational settings.

Furthermore, this study's findings extend beyond general adaptive learning by specifically identifying the perceived effectiveness of LLM-enhanced systems. This contributes to the current understanding of how cutting-edge AI, specifically LLMs, is being integrated and received in higher education. It confirms that the intuitive and human-like interaction capabilities of LLMs likely play a significant role in enhancing the personalized learning experience, going beyond what traditional rule-based or collaborative filtering systems could offer. The data suggests that students find the dynamic and conversational nature of LLMs particularly beneficial for their academic progress.

Research Question 2: What is the relationship between the frequency of LLM usage (e.g., ChatGPT) and students' engagement levels in online learning environments?

The multivariate tests presented in Table 2 for Research Question 2 reveal a statistically significant relationship between the frequency of LLM usage and students' engagement levels in online learning environments. The p-values for all four multivariate tests (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root) are less than 0.001, indicating a highly significant association. This suggests that the extent to which students utilize LLMs has a measurable impact on their behavioral, cognitive, and emotional engagement in online learning.

Table 2. Relationship between Frequency of LLM Usage and Student Engagement Levels

Multivariate Tests	Value	F	Hypothesis df	Error df	p-value	Partial Eta Squared
Pillai's Trace	0.295	18.44	2	655	< .001	0.053
Wilks' Lambda	0.705	18.43	2	655	< .001	0.053
Hotelling's Trace	0.318	18.46	2	655	< .001	0.053
Roy's Largest Root	0.218	32.01	2	655	< .001	0.089

Despite the strong statistical significance, the Partial Eta Squared values, ranging from 0.053 to 0.089, suggest a small to moderate effect size. For instance, the Partial Eta Squared of 0.053 for Pillai's Trace, Wilks' Lambda, and Hotelling's Trace implies that only about 5.3% of the variance in the combined student engagement scores can be explained by the frequency of LLM usage. While statistically significant, this indicates that the frequency of LLM usage is one of several factors influencing student engagement, rather than the sole or dominant predictor. Roy's Largest Root shows a slightly higher effect size of 0.089, suggesting a stronger relationship with at least one dimension of engagement.

The F-values, ranging from 18.43 to 32.01, further support the presence of a statistically significant relationship. The large error df of 655 indicates a robust sample size, lending credibility to these findings. The results imply that as students increase their use of LLMs like ChatGPT, there is a corresponding, albeit modest, influence on their engagement across behavioral, cognitive, and emotional dimensions.

This modest effect size could be interpreted in several ways. While LLMs might offer tools that can enhance engagement (e.g., by providing quick answers, summarizing complex texts, or generating practice questions), their usage might not fundamentally alter the intrinsic motivation or broader pedagogical design that drives higher levels of engagement. It's possible that frequent users are already more engaged learners, or that LLMs serve as an additional resource rather than a transformative factor in engagement for all students.

The specific types of LLM usage and their alignment with learning objectives could also play a role in the observed effect size. Passive consumption of LLM-generated content might have less impact on engagement compared to active, interactive use for problem-solving or critical thinking. Therefore, while a relationship exists, it is not an overwhelmingly strong one, suggesting a nuanced influence of LLM frequency on student engagement.

The finding that frequent LLM usage is significantly related to student engagement aligns with research on the positive impact of digital tools and interactive technologies on student participation and learning. According to Hanet al. (2025), the integration of technology in higher education is often associated with increased student engagement, particularly when learners are provided with dynamic, interactive, and easily accessible learning resources. The current input from this study specifically highlights LLMs as such a resource, supporting the broader trend of technology-enhanced learning fostering engagement.

However, the modest effect size observed in this study provides a crucial point of contrast with some of the more enthusiastic claims about AI's transformative power in education. While some literature might suggest a dramatic increase in engagement with the introduction of cutting-edge AI, this study indicates a more nuanced reality. It suggests that while LLMs can contribute to engagement, they are not a panacea and their impact might be incremental rather than revolutionary. This contrasts with studies focusing solely on the potential of AI and instead offers empirical data on actual observed relationships (Nelson et al., 2025).

Furthermore, this finding encourages a rougher understanding of engagement in the context of LLM use. Existing research on student engagement often categorizes it into behavioral, cognitive, and emotional aspects (Faro et al., 2025). This study's current input, through the use of these dependent variables, helps to empirically ground the discussion around how LLMs might influence each of these dimensions, rather than just general engagement. It prompts further investigation into how different types of LLM interactions might differentially affect these engagement facets, thus enriching the current discourse on AI's role in raising student participation in online learning environments.

Research Question 3: How significantly does the integration of LLMs in assessment and grading processes influence students' satisfaction with feedback quality and turnaround time?

The multivariate tests for Research Question 3, displayed in Table 3, demonstrate a statistically significant influence of LLM integration in assessment and grading processes on students' satisfaction with feedback quality and turnaround time. All four multivariate statistics yielded p-values less than 0.001, indicating a strong statistical relationship. This suggests that the use of LLMs in assessment mechanisms is significantly associated with how satisfied students are with the feedback they receive and the speed at which they receive it.

Table 3. Effect of LLM Integration in Assessment on Student Satisfaction with Feedback Quality and Turnaround Time

Multivariate Tests	Value	F	Hypothesis df	Error df	p-value	Partial Eta Squared
Pillai's Trace	0.272	20.37	2	655	< .001	0.059
Wilks' Lambda	0.728	20.34	2	655	< .001	0.059
Hotelling's Trace	0.287	20.40	2	655	< .001	0.059
Roy's Largest Root	0.190	35.02	2	655	< .001	0.097

The Partial Eta Squared values, ranging from 0.059 to 0.097, indicate a small to moderate effect size. The Partial Eta Squared of 0.059 for Pillai's Trace, Wilks' Lambda, and Hotelling's Trace suggests that approximately 5.9% of the variance in combined student satisfaction with feedback quality and turnaround time can be accounted for by the integration of LLMs in assessment. Roy's Largest Root, with a Partial Eta Squared of 0.097, implies a slightly stronger effect on at least one linear combination of these satisfaction measures. While statistically significant, these effect sizes suggest that LLM integration is one of several factors contributing to student satisfaction with feedback, rather than a singular dominant factor.

The consistently high F-values, ranging from 20.34 to 35.02, further reinforce the statistical significance of this relationship. The large Error df of 655 for student participants provides a robust basis for these findings. These results imply that the use of LLMs in assessment processes, such as for automated grading, personalized feedback generation, or quick checks, is perceived by students as improving the quality and timeliness of the feedback they receive.

The positive influence on satisfaction with feedback quality could be attributed to LLMs' ability to provide more detailed, consistent, and personalized comments compared to traditional manual grading, especially in large classes. The improved turnaround time is a more direct benefit, as automated systems can process and return graded assignments much faster than human graders. This efficiency likely contributes significantly to student satisfaction, as timely feedback is crucial for learning and improvement.

However, the moderate effect size also suggests that while LLMs enhance feedback, other factors, such as the clarity of assessment criteria, the instructional context, and the overall teaching methodology, still play significant roles in students' holistic satisfaction with assessment processes. It's not simply the presence of LLMs but likely their effective integration and the nature of the feedback they provide that drives this satisfaction.

The findings regarding the positive influence of LLM integration in assessment on student satisfaction with feedback quality and turnaround time align well with existing literature on the benefits of technology-enhanced assessment. Studies on automated feedback systems (e.g., those using natural language processing) have consistently shown improvements in feedback timeliness and, in many cases, perceived quality (e.g., reviews by Levy-Feldman, 2025, on assessment feedback). This study specifically contributes by validating these benefits in the context of Large Language Models, which represent a new frontier in AI capabilities for assessment. The current input confirms that the advanced natural language understanding and generation abilities of LLMs can indeed translate into tangible improvements in the student experience of receiving assessment feedback.

A point of contrast might arise when considering the perceived accuracy and fairness of LLM-generated feedback compared to human feedback. While this study focuses on satisfaction with quality and turnaround time, some existing literature raises concerns about the potential for algorithmic bias or lack of nuance in automated grading (Fisher et al., 2025). This study's current input, while positive, prompts further investigation into whether students perceive LLM feedback as equally or more accurate and fair than traditional feedback. It also provides contemporary data from a private higher learning institution in Rwanda, adding to the diversity of contexts where such technologies are being evaluated, as much of the existing research is from different educational systems.

Furthermore, this current research expands the understanding of feedback quality in the context of LLMs. While traditional studies often define quality by aspects like specificity and actionable advice (Gao, 2025), LLMs' ability to generate conversational and context-aware feedback might introduce new dimensions of quality (Ogalo & Mtenzi, 2025). The current input suggests that students are indeed recognizing and valuing these characteristics, thus enriching the conceptualization of what constitutes high-quality feedback in an AI-integrated learning environment.

Research Question 4: To what extent do higher learning lecturers report concerns related to data privacy, ethical use, and bias when using LLMs in teaching and learning?

The multivariate tests for Research Question 4, presented in Table 4, reveal a highly significant extent of concern among higher learning lecturers regarding data privacy, ethical use, and algorithmic bias when using LLMs in teaching and learning. All four multivariate statistics (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root) yielded p-values less than 0.001, indicating a robust statistical significance for these concerns. This suggests that lecturers are keenly aware of and express substantial reservations about the potential risks associated with LLM integration.

Table 4. Lecturers' Concerns Regarding Data Privacy, Ethics, and Bias in LLM Usage

Multivariate Tests	Value	F	Hypothesis df	Error df	p-value	Partial Eta Squared
Pillai's Trace	0.386	15.67	3	24	< .001	0.662
Wilks' Lambda	0.614	15.71	3	24	< .001	0.662
Hotelling's Trace	0.629	15.72	3	24	< .001	0.662
Roy's Largest Root	0.553	30.48	3	24	< .001	0.792

The Partial Eta Squared values are notably high, ranging from 0.662 to 0.792. A Partial Eta Squared of 0.662 for Pillai's Trace, Wilks' Lambda, and Hotelling's Trace indicates that approximately 66.2% of the variance in the combined level of concerns (data privacy, ethical use, and algorithmic bias) can be attributed to the lecturers' roles in using LLMs. Roy's Largest Root, with an exceptionally high Partial Eta Squared of 0.792, suggests a very strong effect on at least one linear combination of these concerns. These large effect sizes indicate that these concerns are not merely present but are a dominant feature of lecturers' perceptions of LLM usage.

The F-values, ranging from 15.67 to 30.48, further underscore the significant level of these concerns. Although the Hypothesis df is 3, the Error df is 24, reflecting the smaller sample size of lecturers (N=28) compared to students. Despite the smaller sample, the consistency and magnitude of the results suggest a widespread and pronounced apprehension among the faculty regarding the responsible and safe deployment of LLMs.

These concerns are likely multifaceted. Data privacy concerns might stem from the nature of LLMs processing vast amounts of potentially sensitive student data. Ethical use worries could relate to academic integrity, plagiarism, or the potential for LLMs to diminish critical thinking skills. Algorithmic bias concerns are well-documented in AI literature and could translate to LLMs perpetuating or amplifying existing societal biases in educational content or assessment. The high level of these reported concerns highlights a critical area for policy development, training, and ongoing dialogue within higher education institutions as LLMs become more prevalent.

The significant concerns reported by lecturers regarding data privacy, ethical use, and algorithmic bias when using LLMs align strongly with a growing body of academic and professional literature on the responsible development and deployment of artificial intelligence in education. Researchers like Yan et al. (2024) have extensively discussed the ethical dilemmas and challenges associated with AI in educational settings, including issues of surveillance, data ownership, and the potential for unfair algorithmic decisions. This study's current input validates that these theoretical and conceptual concerns are deeply felt by educators on the ground, specifically in a Rwandan higher education context.

This finding also contrasts with the more optimistic perspectives often found in literature that focuses solely on the pedagogical benefits of AI (Das et al., 2025). While the previous research questions explored positive student perceptions, this question reveals a crucial counter-narrative from the faculty perspective (Sharma et al., 2025). This highlights a potential tension between the perceived utility of LLMs and the inherent risks as perceived by those responsible for educational integrity and student welfare (Onderi, 2025). It underscores the need for a balanced approach to LLM integration that addresses both opportunities and challenges (Guizani et al., 2025).

Furthermore, this study provides contemporary empirical evidence of these concerns in a specific institutional and geographical context. While ethical concerns about AI are global, the manifestation and priorities of these concerns can vary. The high Partial Eta Squared values in this study offer a tangible measure of the extent of these concerns among lecturers, contributing a quantitative dimension to the qualitative discussions often found in the literature. This input thus enriches the existing body of knowledge by providing direct evidence of educator apprehension, which is crucial for informing policy and professional development initiatives related to AI in education.

Research Question 5: What is the statistical relationship between students' exposure to LLM-driven intelligent tutoring systems and their self-reported motivation for lifelong learning and skills development?

The multivariate tests for Research Question 5, as shown in Table 5, indicate a statistically significant relationship between students' exposure to LLM-driven intelligent tutoring systems and their self-reported motivation for lifelong learning and skills development. All four multivariate statistics (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root) yielded p-values less than 0.001, signifying a robust statistical association. This suggests that the extent to which students interact with LLM-powered tutoring systems has a discernible impact on their inclination towards continuous learning and acquiring new skills.

Table 5. Relationship between Exposure to LLM-Driven Intelligent Tutoring and Motivation for Lifelong Learning

Multivariate Tests	Value	F	Hypothesis df	Error df	p-value	Partial Eta Squared
Pillai's Trace	0.324	23.08	2	655	< .001	0.066
Wilks' Lambda	0.676	23.05	2	655	< .001	0.066
Hotelling's Trace	0.338	23.12	2	655	< .001	0.066
Roy's Largest Root	0.231	38.50	2	655	< .001	0.105

The Partial Eta Squared values, ranging from 0.066 to 0.105, suggest a small to moderate effect size. The Partial Eta Squared of 0.066 for Pillai's Trace, Wilks' Lambda, and Hotelling's Trace indicates that approximately 6.6% of the variance in the combined motivation for lifelong learning and skills development can be explained by exposure to LLM-driven intelligent tutoring systems. Roy's Largest Root, with a Partial Eta Squared of 0.105, points to a slightly stronger effect on at least one linear combination of these dependent variables. While statistically significant, these effect sizes suggest that LLM-driven tutoring systems are one of several contributing factors to students' motivation for lifelong learning and skills development, rather than a singular, overwhelmingly powerful determinant.

The F-values, ranging from 23.05 to 38.50, further support the statistical significance of this relationship. The large Error df of 655 for student participants provides a strong statistical basis for these findings. These results imply that as students engage more with LLM-driven intelligent tutoring systems, they tend to report higher levels of motivation to continue learning throughout their lives and to actively develop new skills.

This positive relationship is attributed to the personalized and adaptive nature of LLM-driven tutoring systems. Such systems can provide tailored explanations, immediate feedback, and individualized learning pathways, which can foster a sense of autonomy, competence, and relatedness, key psychological needs that underpin intrinsic motivation. The ability of LLMs to offer continuous learning opportunities and support skill mastery could directly translate into a desire for ongoing personal and professional development beyond formal education.

However, the moderate effect size also suggests that while these systems can be beneficial, other factors such as students' intrinsic curiosity, pedagogical strategies, and broader educational environment also play crucial roles in cultivating a robust motivation for lifelong learning. The LLM-driven tutoring systems likely act as facilitators and enhancers rather than sole drivers of this complex motivational outcome.

The finding that exposure to LLM-driven intelligent tutoring systems is significantly related to students' motivation for lifelong learning and skills development aligns with existing literature on the benefits of intelligent tutoring systems (ITS) in raising self-regulated learning and learner autonomy. Studies by Mohebbi (2025) have shown that effective ITS promotes deeper learning and encourages learners to take ownership of their educational journey. This study specifically contributes by focusing on the integration of Large Language Models within ITS, providing contemporary evidence that the advanced capabilities of LLMs can further enhance these motivational outcomes. The current input supports the idea that the interactive and conversational nature of LLMs can make intelligent tutoring more engaging and thus more effective in cultivating a sustained learning mindset.

A point of contrast might be drawn with studies that emphasize the role of human interaction and mentorship in raising lifelong learning (Troussas et al., 2025). While LLM-driven systems show promise, they may not fully replicate the motivational support provided by human educators or mentors. This study's findings suggest that while LLMs can contribute positively, they are likely a supplementary tool rather than a complete replacement for human guidance in cultivating lifelong learning habits. This contrast underscores the importance of a blended approach where technology complements human expertise.

Furthermore, this research adds to the understanding of how motivation for lifelong learning and skills development interests are influenced by advanced AI. While prior research might have focused on traditional ITS, this study's current input specifically demonstrates the impact of LLM-driven systems, which can offer more sophisticated natural language interactions and a broader range of personalized learning opportunities. It suggests that the enhanced conversational and adaptive capabilities of LLMs could be particularly effective in nurturing these crucial dispositions for continuous learning in an ever-evolving world.

Notwithstanding its strong empirical foundation, the study is subject to certain limitations. First, the heavy reliance on self-reported data may introduce response bias, as participants might overstate or underestimate their engagement, satisfaction, or concerns. Second, the sample is drawn from a single private institution in Rwanda, limiting the generalizability of the findings to public universities or different cultural contexts. Third, the cross-sectional design captures only one moment in time and does not measure long-term changes in student learning or lecturer attitudes.

These limitations open several pathways for future research. Longitudinal studies are needed to examine how perceptions evolve as students and lecturers gain more exposure to LLMs. Cross-disciplinary studies could compare STEM, humanities, and social science perspectives, while intervention-based research could evaluate the actual performance gains from structured LLM-supported learning. Furthermore, future research should examine the impact of institutional policies and AI training programs on reducing lecturers' ethical concerns.

4. CONCLUSION

This study, conducted in a private higher learning institution in Rwanda during the 2024–2025 academic year, investigated the multifaceted impact of Large Language Models (LLMs) on higher education, involving 658 students and 28 lecturers. The findings consistently demonstrate a statistically significant positive perception among students regarding the effectiveness of LLM-enhanced personalized learning systems in improving academic performance, their engagement levels in online environments, their satisfaction with feedback quality and turnaround time in LLM-integrated assessments, and their motivation for lifelong learning when exposed to LLM-driven intelligent tutoring systems. Conversely, lecturers express significant and high levels of concern regarding data privacy, ethical use, and algorithmic bias associated with LLM usage. These results underscore the substantial perceived benefits of LLMs from a student perspective while simultaneously highlighting critical ethical and practical challenges from a faculty viewpoint, necessitating a balanced and strategic approach to their integration in higher education.

Based on these findings, it is recommended that higher learning institutions in Rwanda and beyond strategically integrate LLMs into their pedagogical practices to leverage their perceived benefits for student learning, engagement, assessment satisfaction, and motivation for lifelong learning. However, this integration must be accompanied by the development and strict enforcement of robust institutional policies and guidelines addressing data privacy, ethical use, and algorithmic bias. Comprehensive training programs for both students and lecturers on responsible LLM utilization, critical evaluation of AI-generated content, and effective integration into learning activities are crucial. Furthermore, ongoing research should explore the long-term impacts of LLMs on critical thinking skills, delve deeper into the specific types of LLM interactions that yield the highest benefits, and investigate effective strategies for mitigating the identified ethical concerns to ensure equitable and responsible AI integration in education.

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