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Generative AI Literacy and Students' Academic Performance: The Mediating Role of Student Engagement in Higher Education

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Abstract

Purpose: *The study investigates the effectiveness of Generative AI Literacy, which includes Technical Proficiency, Critical Evaluation, Ethical Awareness, Creative Application in influencing the academic performance of postgraduate management and education students. It also addresses the mediating role of the student engagement in the learning outcomes in the higher education.*

Methods: *The sample was 197 postgraduate students of different stream in Kapilvastu District. Descriptive and Explanatory research design has been used to conduct the study. The questionnaire was a structured questionnaire with 7 points Likert scale used to collect data. PLS-SEM was used to evaluate the relationship between variables.*

Results: *The findings indicate that Generative AI Literacy is an important indicator of academic performance (0.486). Embracing technical excellence and creative application not to mention other factors have the largest factor loadings but other factors including critical evaluation and ethical awareness have also made a substantial contribution. AI literacy (0.516) had a positive influence on the student engagement (0.266) and, therefore, student academic performance (0.209). The mediation analysis has established that there is indeed such a thing as student engagement being a mediator of relationship between AI literacy and academic success and that student endowed with high AI competencies are most likely to be active hence more successful in their performance.*

Implications: *Higher education institutions need to implement structured AI literacy programs, ethical/critical use of AI tools and models of teaching that are engagement-based in order to foster academic excellence in an AI-infused learning environment.*

Originality: *The present study is among the pioneer studies involving the application of PLS-SEM to test the multidimensional nature of Generative AI Literacy and its mediated effect on student engagement in academic performance in the environment of higher education within Nepal.*

Keywords: Generative AI Literacy, Student Engagement, Academic Performance, Higher Education, PLS-SEM.

1. Introduction

Generative AI technologies revolutionize education systems in the world like never before and the opportunity comes with both unprecedented opportunities and a lot of problems to institutions of higher education. Due to the high frequency of AI-based tools implementation in the universities regarding the purposes of teaching, learning as well as facilitating, the possibility of the users to approach the technologies in a proper manner (which is denoted as the Generative AI Literacy) has been made to actualize as a factor of academic accomplishment (Zawacki-Richter et al., 2024). This proficiency extends much further than ordinary digital proficiency; in addition to technical abilities, one must be capable of critically analyzing the contents created by the AI, be ethically aware of its utilization, and use it creatively to solve problems, not to mention to generate creative solutions (Long & Magerko, 2020). Since we are talking about the AI-propped learning scenarios, it is necessary to determine how the competencies of students in this regard affect their interest and academic achievement.

Traditional and effective study habits or the quality of teaching do not entirely influence the performance of the students at the tertiary level of education as it used to be before. On the contrary, the scholarly community believes that the existence of AI-facilitated spaces has led to the creation of novel types of cognitive, behavioral, and emotional interaction, which consequently affect learning paths (Nguyen et al., 2024). Using the assistance of Generative AI systems like ChatGPT, Generative style, and Copilot, students can better understand material on complex subjects, receive instant feedback, generate new ideas, and, therefore, study the course material more productively. The reality though is that these benefits will not be forthcoming until students receive adequate literacy capabilities to process AI outputs in responsible and critical manner (Porayska-Pomsta, Holmes & Nemorin, 2024). Therefore, academic performance of students is increasingly turning out to be dependent on their capability to apply AI in an ethical, correct, and innovative manner.

The global research community has considered student engagement to be one of the most critical elements, and it has served as a link between the application of technology and student learning outcomes (Bergdahl et al., 2024). Deep learning, as well as, long-term academic success requires participation of cognitive, behavioral, and affective dimension of the student. In this situation, when students are equipped with AI to help them in their learning process, they become more active, ask questions, attempt, answer more and become more motivated by what they are learning (Ezeoguine & Eteng-Uket, 2024). Conversely, with low levels of AI literacy, the risk is that the students would find themselves in a situation where they over-rely on AI, receive misinformation, engage in academic malpractices, or become mentally disengaged. Therefore, universities and colleges worldwide are investing in AI literacy as one of the moves to encourage student engagement and enhance their academic performance.

Although the use of generative AI in the academic sector is gaining traction in South Asia, the adoption of AI in the field is also being hampered by infrastructure challenges including the lack of digital infrastructure, healthcare disparity, and institutional inadequacy (Henadirage & Gunarathne, 2024). Although the region is becoming digitalized, many learning institutions are discovered to be working with the previous education systems which are not taking the advantage of AI in promoting learning among students. This, in its turn, causes the unequal performance of the students in the field of AI literacy, and, therefore, their interest and academic development. The study conducted in India, Bangladesh, and Sri Lanka demonstrates that graduate management students are adopting the use of generative AI in academic writing, making decisions, and interpreting data and becoming more creative, yet, struggle with criticism evaluation and ethical consciousness (Yusuf, Pervin & Román-González, 2024; Henadirage & Gunarathne, 2024). Therefore, these gaps are indicative of the necessity to question the scope and modalities, through which AI literacy dimensions may affect the student learning experiences in changing educational settings.

Higher education in Nepal is quickly becoming digitized. The most significant reasons that have primarily led to the change are post-pandemic reforms, the growth of learning management systems, and the growing knowledge of AI-based tools (Ghimire et al., 2024). Nonetheless, the degree to which students and institutions are ready to embrace the use of generative AI is quite dissimilar in both cases. Many Nepalese students assign tasks, prepare exams, review literature, and clarify concepts with the help of AI, but they are not given a systematic teaching step by step on the critical and ethical points of this tool usage (Adhikari, 2025). According to the most recent research, the students of Nepal are facing problems with verification of AI-generated material, understanding restrictions, preventing plagiarism, and applying AI in a creative manner to solving academic problems (Mah & Groß, 2024). Consequently, the access to AI has a rather limited impact on their educational achievements not only because it is not a factor but also because the way they will perform the responsible and successful use of AI.

Furthermore, the level of student participation in Nepal universities is not necessarily pleasant. The scientists opine that usage of AI tools has increased the number of learning tasks performed, but the involvement is largely superficial, with the students adopting the tools due to convenience and not in-depth learning (NAAMII, 2025). Without proper preparation of students in terms of AI literacy, they might choose to omit the process of critical thinking, and, subsequently, they will over-use AI-generated content, which will eventually lead to the reduction of the level of their active engagement into the learning process. The primary issue that this situation implies is that technologically-supported learning conditions will inadvertently extend the performance gap should the students not be equipped with the competencies of AI. Thus, the implementation of holistic AI literacy that combines technical, ethical, evaluative, and creative skills is invited to schools to foster the involvement in the process of learning and the success in the academic outcomes.

Although such an international body of literature has grown with respect to the use of AI in higher education, how multidimensional generative AI literacy applies to academic performance in the South Asian settings has yet to be answered in detail. Most of the current research is based on descriptive research or considers separate variables such as digital literacy or frequency of AI use without exploring the more complicated aspects such as technical competence, critical thinking, ethical consciousness, and creative use (Long & Magerko, 2020). An obvious lack of empirical research incorporating strong analytical models exists. In addition to that, in spite of the fact that student engagement is typically regarded as one of the most potent predictors of the learning results, only a small number of studies investigate its application as a mediating factor in the relationship between AI literacy and academic achievement. There is hardly any real-world data that is available in Nepal on the application of generative AI within the educational context. Currently, no elaborate framework has been developed to integrate multidimensional AI literacy and student interactions to predict academic outcomes. Majority of the existing works have been relying on just the traditional regression techniques that are not sufficient to capture the complex interactions between the behavioral, cognitive, and technological variables. This research gap in methodology explains why more sophisticated analytical procedures like the Partial Least Squares Structural Equation Modeling (PLS-SEM), which enables the assessment of measurement validity and structural correlations concurrently, are needed (Hair et al., 2021). PLS-SEM is most suitable to such an innovative concept as AI literacy in which the conceptual framework is still emerging and the model is complex.

Due to these gaps, the proposed study seeks to discover the relationship between Generative AI Literacy, which is characterized by Technical Proficiency, Critical Evaluation, Ethical

Awareness, and Creative Application, and academic achievement among postgraduate management students in Nepal and the role played by Student Engagement as mediator. This study, which analyses the data on a large sample of students in the Kapilvastu District with the help of PLS-SEM, is one of the first empirical models in Nepal which, on the one hand, demonstrates the multidimensional character of AI literacy, and, on the other hand, its further impact on student engagement and performance. The research is a treasure trove of information to teachers, administrators, and colleges deciding to add AI to supplement higher education in a sustainable and efficient way. The significant one is to test how student dropout intention among postgraduate management students in Nepal is determined. The study research objectives are specific and are based on the following:

RO1: To investigate the intervention of Technical Proficiency, Critical Evaluation, Ethical Awareness, Creative Application on Generative AI Literacy in institutions of higher learning.

RO2: To quantify the impact Generative AI Literacy on the Student Academic Performance in higher education institutions.

RO3: To investigate the mediating role of Student engagement between the relationship Generative AI Literacy on Student Academic Performance in institutions of higher education.

2. Literature Review

Theoretical Review

Technology Acceptance Model (TAM) that was advanced by Davis (1989) explains that he must find the technology easy to use and useful to him to accept it. With regards to the generative AI, it can be reformulated as follows: students are to see AI tools as a necessity and an easy cake as something that is leading in the technical skill and knowledge of its merits and, thus, they will most likely be proactively engaged in the process. Such an interaction will, actually, improve academic performance in a feedback loop.

Coming along with this, Constructivist Learning Theory, which was introduced by Piaget (1972) and expounded upon by Vygotsky (1978) observes that the students are most effective in constructing knowledge through their active interaction and not through taking instructions. Generative AI is a perfect example of constructivist tool due to its ability to learn discovering, testing, and learning new concepts. The AI as a learning companion helps the students become more engaged during the classroom session, which does not only increase the engagement but also provides better results. Thus, TAM and Constructivist

Learning Theory are sequential conclusions of how perception of the AI usefulness in learning and engagement via AI leads to a deeper learning experience and academic success.

Conversely, Self-Regulated Learning Theory (Zimmerman, 1989) continues to indicate that the capability of learners in setting goals of their educational processes, keeping track and assessing the results is an important dimension of learning that Self-Regulated Learning Theory (Zimmerman, 1989) emphasizes. Generative AI Literacy is a curriculum that makes students responsible consumers of technology by enabling them to assess AI-generated work critically, determine its accuracy, and adhere to ethical standards that usually makes responsible students become self-directed learners. It is a self-regulation that is a force of engagement and which ultimately leads to good academic performance.

To top that, there is a theory referred to as Cognitive Load Theory (Sweller, 1988) which is concerned with unlearning such that, unnecessary mental effort is a hindrance to the learning process and therefore to learning efficiency, the effort must be less. AI literate students, particularly those that are critical evaluators, have an easy time filtering out the irrelevant information and then neglecting the irrelevant information and at the same time filter out on the meaningful information to work on which will result in the elimination of cognitive overload. This easy processing ensures that learners are occupied and the probability of greater success is exposed to them. Concisely, according to both SRL and CLT, AI literacy can be described as a key that opens the gates to effective, focused and self-directed learning among other theories.

Finally, but not least, it is known as Engagement Theory (Kearsley & Shneiderman, 1998) that claims that the most significant learning is the one where students develop creative, collaborative, and technology-based activities. Generative AI Literacy is an ideal facilitator of such activities in which students are given the opportunity to be creative and innovative in using AI tools, work in teams, and engage with course content actively. This increased the involvement forms a connection between AI literacy and academic performance, thereby, is highly significant to the mediation in the proposed model.

Concisely, the above theories are converting to one main point, which is multidimensional AI literacy-technological, ethical, evaluative and creative areas of competence are collections of skills that enable students to learn actively, self-manage their learning, offload their cognitive load, immerse themselves in the process and that is what is going to result in a successful academic outcome.

2.2 Empirical Review

H1a: Generative AI Literacy is positively and significantly impacted by Technical Proficiency.

Technical Proficiency - being capable of using the generative AI tools is one of the principal foundations of AI proficiency. According to Zhai and Lu (2023), once the students learn good operational skills in AI systems, they become even more literate as they are not only using AI but also knowing how it works. However, Long and Magerko (2020) also note that by developing technical skills users develop the required self-confidence and, therefore, they apply AI in a more task-oriented manner, which makes their general competence even more effective. Another concept introduced by Kasneci et al. (2023) is that AI-related knowledge regarding AI interface and features can be a tremendous boost to the willingness of students to learn with AI. Continuing on this point, Naamati-Schneider and Alt (2024) claim that the technological skills do not remain an addition, but the prerequisite in using technology in such a manner that they shape the perception and usage of the AI-generated knowledge by the learners. All these studies are part of the thesis that one of the most important implications of Generative AI Literacy emergence may be regarded as technical expertise.

H1b: Critical Evaluation positively and significantly impacts Generative AI Literacy.

The existence of the group Critical evaluation -the power to check the truthfulness and demand the accuracy of the data generated by the AI- was one of the key elements of the AI user group that in the environment of achieving Generative AI Literacy was identified as a fundamental concept. Holmes and Zhgenti (2024) assume in their article that students who participate in questioning AI-generated are in a better position because they learn the knowledge of both sides, that is, the benefits and drawbacks of the provided tools. Similarly, according to Kasneci et al. (2023), evaluative skills development reduces the susceptibility to misinformation and assists in the propagation of conscious and responsible usage of AI. According to Dwivedi et al. (2023), the future outcomes of the AI-generated content verification process are the heightened state of mental preparedness that, consequently, enables the students to adhere to the list of moral rules and use AI in the most effective manner. Expanding on this argument, Zawacki-Richter and Jung (2023) take critical thinking as applied to AI output as one of the primary determinants of the competency in

AI in the digital learning setting. All these works are united in the opinion that critical assessment is a significant part of Generative AI Literacy.

H1c: there is a positive and significant impact of Ethical Awareness on Generative AI Literacy.

Ethical awareness, which involves receiving how the AI is used in the respectful, objective, and ethical manner, has become one of the important aspects of the AI issue. Kong et al. (2023) also concluded that the ethical aspect provides students with the correct academic application of AI tools that result in the further enrichment of their level of literacy. As informed by Dwivedi et al. (2023), a broad interpretation of the bias in algorithms, confidentiality concerns, and academic dishonesty is the key that results in more responsible AI actions. The same is true of Wang et al. (2025) who declared that students guided by the morality principle in AI are more literate because they being critical detach themselves of system dependency. Furthermore, Holmes and Zhgenti (2024) also give reasonable attention to the fact that students who realize the potential ethical risk are also more knowledgeable about AI and become more capable of using it in the safe way. This fact is connected to the awareness of ethics that is also a significant element of achieving the AI literacy.

H1d: Generative AI Literacy is positively and significantly influenced by Creative Application.

The Creative application is the most significant predictor of AI literacy and can be used by the user because an AI tool that one can rely on to engage in innovative problem-solving, ideation, or even simplify academic activities is the Creative one. Wang et al. (2024) discovered that more competent students creatively applied AI since they explored the untapped potential of AI systems. In the same manner, Long and Magerko (2020) believed that the creativity with AI expanded the knowledge of students regarding the generative functions, which consequently enhanced their general competence. In addition to that, Zhai and Lu (2023) found out that creative playing with AI tools made users more flexible and did result in deeper learning. Besides this, Wang, Sun, and Chen (2023) also indicated that the students who used AI to generate new ideas, simulate, or solve problems were in a better position to control academic and technical literacy. That is why, the creative application could be regarded as one of the primary factors, which influences Generative AI Literacy positively.

H2: The Generation AI Literacy positively and significantly affected Academic Performance of Students.

The high rate of AI literacy among the students of the university is proved by the empirical evidence that results in the academic success of the students. As an example, Bećirović et al. (2025) have demonstrated that the AI-literate students turn out to be the authors of the academic work of higher quality as they understand it deeper, get feedback, and perform the analysis themselves. Similarly, the study by Wang, Sun, and Chen (2023) showed that the AI literacy skills result in better reasoning, interpretation, and conceptual clarity, which subsequently improve academic outcomes. According to Sherwood and Mac Donald (2024), postgraduate students with AI literacy ability are better placed to deliver their assignments without errors and, therefore, better graded. Also, in the scenario involving Nepal, Ghimire et al. (2024) established that AI-competent learners are adequately equipped to engage in digital academic activities and, therefore, exhibit increased academic performance. Overall, all these pieces of research discover that AI literacy is a significant predictor of academic success.

H3: Student Engagement mediates between Generative AI Literacy and Academic Performance of Students.

Involvement of students in education is widely acknowledged as the central element that helps to explain how AI literacy will result in higher academic achievement. Bergdahl et al. (2024) put forward the idea that a competent user of a certain AI could exhibit increased rates of the three aforementioned engagement types - cognitive, behavioral, and emotional - as a competent AI user feels more confident and comfortable when using AI tools. The same was found by Nguyen et al. (2024) when they wrote that good AI literacy students are more active in learning activities and consequently, they have enhanced the degree of engagement. That is why Panadero et al. (2023) indicated that the concept of engagement is inherently connected to deeper processing and, therefore, better academic performance therefore taking up the mediation role. In Nepal, NAAMII (2025) recommends that students can use AI-assisted learning activities to reach higher academic goals. Thus, this whole evidence is leading to a single direction, i.e., the mediation of the relationship between the AI literacy and academic performance by the student engagement.

3. Research Methodology

3.1 Research Design

The study is designed with the quantitative method of study, which has a descriptive and explanatory component. The descriptive part is intended to document the perceptions of postgraduate students on four important dimensions of Generative AI Literacy that are Technical Proficiency, Critical Evaluation, Ethical Awareness and Creative Application, as well as their levels of Student Engagement and Academic Performance. The guided explanatory element, which is directed by positivist paradigm, is the confirmation of a structural model where AI Literacy is the exogenous that causes Student Engagement, which in turn causes Academic Performance. The two forms of answering the research question can hence be simultaneously performed here i.e., what the AI-related competencies of the students are, causal direction and strength of the relationships between the key learning variables. The choice of PLS-SEM is explained by the possibility to work with complex models, predictive quality and the possibility to fit new constructs like AI literacy in higher education research.

3.2 Population and Sample

The study sample involved 197 postgraduate students who were pursuing different streams in institutions of higher learning in the Kapilvastu District. It has four institutions of postgraduate programs in various streams: Kapilvastu Multiple Campus in Taulihawa Municipality with 55 students; Siddhartha Campus in Banganga Municipality with 90 students; Buddhabhumi Campus in Buddhabhumi Municipality with 50 students; and Nepal Adarsh Multiple Campus in Shivraj Municipality with 2 students. Therefore, a total of 197 postgraduate students in these campuses in the Kapilvastu District will represent the study population. The sample size is also 197 since the study uses census approach.

3.3 Instrument Design and Measurement

The questionnaire used to collect the data included all the questions rated on a 5-point Likert scale that was highly disagree to strongly agree. The instrument had five items in every dimension of the four dimensions of Generative AI Literacy, Technical Proficiency, Critical Evaluation, Ethical Awareness, and Creative Application, thus, had a total of twenty indicators, that reflected the higher-order Generative AI Literacy construct. On the one hand, the authors received these items as per the various sub-elements of the AI competence framework (Long & Magerko, 2024), the critical assessment of the outputs of generative AI (Holmes, 2024; Kasneci et al., 2023), and the use of AI systems to education in an ethically responsible manner (Dwivedi et al., 2023). The mediating variable introduced was Student Engagement, the measurement of which consisted of four indicators that included behavioral, cognitive, and emotional scales, as well as consistent with the scales of engagement that are usually used in the research conducted in the higher education (Fredricks, Blunden, & Paris, 2004; Bond et al., 2023). Five self-report questions were used to measure the academic performance and the questions measure perceived learning achievements, quality of academic work and success in coping with course demands, which are in line with the performance measurement strategies, which are widely shared among educational institutions (Zhang & Chen, 2023). In order to ensure that the questionnaire possesses a positive level of content validity, the senior academic professionals in the field of digital learning and AI literacy were involved in the review of the questionnaire. In order to make the items more understandable, the consistency of the test and the response patterns were to be experimented using the pilot test with 30 postgraduate students to know whether the respondents were answering according to the psychometric expected course or not. The feedback that was received during the pilot stage resulted in certain adjustments in the phrasing, and, consequently, the overall functionality of the final tool has been improved, as well as its comprehensibility.

3.4 Data Collection Procedure

The information required in the study was obtained using various methods of self-completed questionnaires. These were distributed on paper and electronically to have easy access and suitability of meeting the preferences of the students. The management of the institution was consulted before the distribution of the survey and the participants informed of the objectives of the study, the confidentiality of their answers and how voluntary the survey would be. The principles of ethics like confidentiality and anonymity were applied in order to decrease the bias of responses and allow the genuine involvement. The completed questionnaires were actually collected using the final copy of the questionnaires following the feedback of the pilot test. Data collection was done in a period of four weeks where the necessary responses were acquired among the students of the chosen institutions in an organized manner.

3.5 Data Analysis

To begin with, descriptive statistics had been conducted to represent the demographic profiles of the respondents and their opinions regarding AI literacy, engagement, and academic performance. This was preceded by the evaluation of the measurement model with an objective of confirming that the constructs were dependable and valid. As a matter of fact, it entailed the testing of Cronbachs alpha, Composite Reliability (CR) and Average Variance Extracted (AVE) as measures of convergent validity. Discriminant validity was established by using the Heterotrait Monotrait Ratio (HTMT) and the Variance Inflation Factor (VIF) values proved that there was no problem of multi collinearity. Subsequently, the structural model was tested in terms of the associations between the constructs tested. Bootstrapping using 10,000 resamples to produce t-values, path coefficients and p-values to test the effects was done. Coefficient of determination (R^2) of Student Engagement and Academic Performance was also used to measure the explanatory power of the model. It is through this exhaustive process of data analysis that enabled the researchers to build a very solid argument to support their results, which were statistically significant and aligned with the theoretical model that relates Generative AI Literacy to student engagement and academic performance.

4. Results and Analysis

4.1 Measurement Items Assessment

Table 1 : *Assessment of measurement scale items*

Items	Outerloading	VIF	Mean	S.D
AP1	0.965	1.56	3.615	0.844
AP2	0.902	2.02	3.571	0.835
AP3	0.735	1.603	3.214	0.96
AP4	0.911	1.751	3.512	0.906
AP5	0.902	1.652	3.571	0.835
CA1	0.738	1.419	3.746	1.072
CA2	0.588	1.149	3.623	1.09
CA3	0.671	1.365	3.889	0.715
CA4	0.783	2.372	3.873	0.654
CA5	0.773	2.426	3.865	0.653
CE1	0.978	1.431	3.016	0.895
CE2	0.778	1.932	3.147	0.987
CE3	0.916	1.431	2.79	1.039
CE4	0.918	1.325	2.865	1.049

CE5	0.897	2.451	2.885	0.999
EA1	0.937	1.231	3.659	0.715
EA2	0.568	1.105	2.944	0.907
EA3	0.779	3.619	3.563	0.859
EA4	0.812	3.431	3.734	0.857
EA5	0.809	3.84	3.746	0.786
SE1	0.901	3.082	3.163	1.009
SE2	0.909	3.319	3.147	1.015
SE3	0.845	2.391	3.278	1.307
SE4	0.915	3.343	3.222	1.007
TP1	0.974	1.149	3.679	0.764
TP2	0.778	2.876	3.663	0.956
TP3	0.862	3.401	3.536	0.94
TP4	0.852	3.208	3.448	0.972
TP5	0.806	2.505	3.56	0.964

Table 1 indicates the extent to which the various items were measured successfully which were used to measure the constructs to be investigated in the research - Academic Performance (AP), Creative Application (CA), Critical Evaluation (CE), Ethical Awareness (EA), Student Engagement (SE), and Technical Proficiency (TP). The overwhelming majority of the outer loadings show that most of the indicators have a high enough level of item reliability since most of them are over the minimum cutoff of 0.70 (Hair et al., 2021). Some items that are slightly lower than the standard mark are however not removed such as CA2 (0.588) and EA2 (0.568) but the Average Variance Extracted (AVE) of the construct is at least 0.50 (Fornell and Larcker, 1981). As such, a relatively large AVE value of CA and EA than the reference signifies that they do not have the significant contribution of their constructs in the presence of convergent validity despite moderately loading indicators. The Variance Inflation Factor (VIF) of the individual measurement items does not exceed the acceptable Maximum of 5.0, therefore, showing that there is no issue of multicollinearity between the indicators and the model estimates are stable (Sarstedt et al., 2017). That is, this confirms that no measurement item is measured too much in relation to the other and thus the reflective measurement model is safe. The fact that the mean values and the standard deviations are quite high also testifies to the fact that the views of the respondents were sufficiently varied. The mean values of the items are in the range of approximately 2.79-3.89, the standard deviation values are in the range of 0.65-1.30, hence, providing the adequate dispersion and no evidences of the uniformity and bias of the responses. This kind of variability is in line with the perceptions of the participants and, therefore, their reliability also increases among the six constructs. The measurement scales have been good in psychometric terms according to the results that have been obtained when considered collectively. The items in the cluster have been reliable enough, loading values have been found acceptable, and no problem of multicollinearity has been observed, therefore, justifying their acceptability in subsequent structural model analysis.

4.2 Quality Criteria Assessment

Table 2 : *Construct Reliability and Validity*

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AP	0.93	0.937	0.948	0.786
CA	0.756	0.752	0.838	0.51
CE	0.94	0.942	0.955	0.81
EA	0.84	0.837	0.889	0.62
SE	0.915	0.926	0.94	0.797
TP	0.908	0.918	0.932	0.734

The summary of the internal consistency of the six latent variables and their convergent validity i.e. Academic Performance (AP), Creative Application (CA), Critical Evaluation (CE), Ethical Awareness (EA), Student Engagement (SE) and Technical Proficiency (TP) is summarized in Table 2. The values of Cronbach alpha in each of the cases exceed the recommended minimum of 0.70, thereby confirming high internal reliability of the constructs (Hair and Alamer, 2022). The scores range between 0.756 of CA and 0.940 of CE, and, therefore, can show the consistency in the level of each construct items elevating the same idea. All scores of composite reliability (rho c which has been considered as a better measure than Cronbach alpha) stand over the 0.70 mark with the lowest and highest points being 0.838 and 0.955 respectively. This coincides with the internal consistency of the constructs. Concerning the convergent validity, the values of Average Variance Extracted (AVE) are 0.510 (CA) and 0.810 (CE), and in all the cases they are more than the required amount of 0.50 (Fornell & Larcker, 1981). These results suggest that all the factors can explain to a bigger part than a half of the variance of the indicators, and therefore, 3 measures of Generative AI Literacy, Student Engagement, and Academic Performance are correct. Simply put, Table 2 is supporting the idea that the measurement scales have the reliability and convergent validity, therefore, they can be used in the further structural analysis.

4.3 Discriminant Analysis

Table 3 : *Heterotrait-Monotrait ratio of correlations*

Variables	AP	CA	CE	EA	Gen AI Literacy	SE	TP
AP							
CA	0.553						
CE	0.331	0.386					
EA	0.419	0.526	0.58				
SE	0.479	0.448	0.418	0.459	0.564		
TP	0.628	0.651	0.364	0.401	0.822	0.412	

Table 3 demonstrates Heterotrait-Monotrait (HTMT) ratios that were utilized to assess the discriminant validity of the latent constructs. In addition, all the values of the HTMT are below the 0.90 mark (Henseler et al., 2015) that means that the constructs are distinctly empirically different. The most significant correlation is between Technical Proficiency and Generative AI Literacy (0.822) whereas the other ones such as CE and EA (0.580) or SE and CE (0.418) are moderate and well within the acceptable ranges. The statistical significance of the values of these given indicators reveals that the constructs that are theoretically connected do not yet indicate an offensive conceptual coincidence. Such division ensures that every construct depicts a distinct dimension of the conceptual model. Additionally, the low HTMT ratios decrease chances of occurrence of multicollinearity hence raise the degree of confidence in the validity of structural paths that are tested in the subsequent analyses. Thus, the HTMT results represent the necessary requirement of SEM interpretation because they endorse the hypothesis that the measurement framework is discriminant valid.

4.4 Model Fit

Table 4 : *Model Fit Indices*

	Saturated model	Estimated model
SRMR	0.065	0.068
d_ULS	0.854	0.874
d_G	n/a	n/a
Chi-square	∞	∞
NFI	.912	.932

Table 4 shows the global indices of fit of saturated and the estimated models of the structural model. The values of Standardized Root Mean Square Residual (SRMR) 0.065 in the saturated model and 0.068 in the estimated model are significantly lower than the maximum value of 0.08, which proves that the model is tightly approximately fitted and has only very few residuals (Hair & Alamer, 2022). The Normed Fit Index (NFI) values are 0.912 (saturated) and 0.932 (estimated) which is greater than 0.90 hence the good comparative fit with the null model. The measure between saturated and estimated values shows that the structural model is stable and well-specified. Although the values of d ULS are mediocre (0.854-0.874), they are acceptable in PLS-SEM that does not mandate an exact fit. Overall, the model-fit measures prove to be strong evidence that the structural model is consistent with theory, empirically sound, and can be used to test the hypothesis.

4.5 Hypothesis Testing

Table 5 : *Hypothesis Testing Using Bootstrapping*

Hypothesis	Path Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1d	**CA -> Gen AI Literacy**	0.244	0.243	0.02	11.995	0	Accepted
H1b	**CE -> Gen AI Literacy**	0.375	0.373	0.026	14.678	0	Accepted

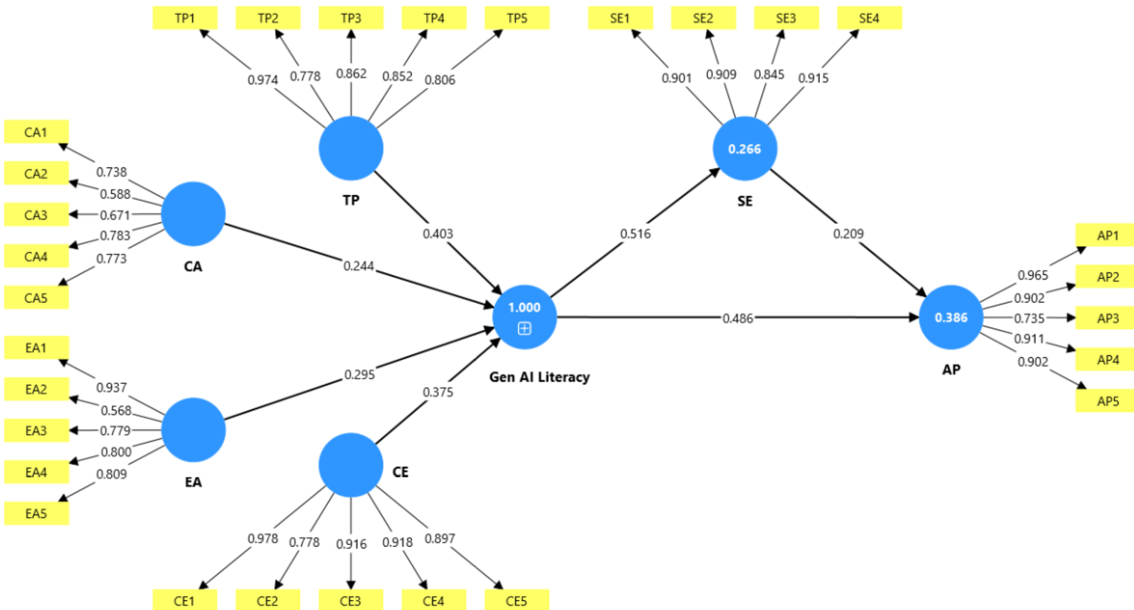
H1c	**EA -> Gen AI Literacy**	0.295	0.294	0.023	12.729	0	Accepted
H2	**Gen AI Literacy -> AP**	0.486	0.49	0.05	9.673	0	Accepted
	Gen AI Literacy -> SE	0.516	0.518	0.047	11.071	0	
	SE -> AP	0.209	0.207	0.06	3.511	0	
H1a	**TP -> Gen AI Literacy**	0.403	0.403	0.029	13.879	0	Accepted
H3	**Gen AI Literacy -> SE -> AP**	0.108	0.107	0.033	3.303	0.001	Accepted

R-square = 0.386 R-square adjusted = 0.381

The bootstrap results, which help to discuss the structural relationships between the variables under study, are presented in Table 5. All the path coefficients are statistically significant at $p < 0.001$ and that is the data highly supports the hypotheses proposed. Technical Proficiency is the variable that positively influences Generative AI Literacy to the greatest extent among the other variables of the predictors (β = 0.403, t = 13.879), which, in its turn, proves the use of technology as a foundation of AI competence. In addition to that, the other three factors, which are also the sources of the concept of AI literacy, are Critical Evaluation (β = 0.375, t = 14.678), Ethical Awareness (β = 0.295, t = 12.729), and Creative Application (β = 0.244, t = 11.995), all considerably weighted, which demonstrates the multidimensionality of AI literacy. Generative AI Literacy has a very close connection with Academic Performance (β = 0.486, t = 9.673) which is the central concept of the concept that AI competence will result in improved academic performance. Also, Student Engagement is significantly determined by AI Literacy (β = 0.516, t = 11.071) since the former can affect and influence the learning process in both motivation and behavior. As a construct, Student Engagement makes a considerable impact on Academic Performance (β = 0.209, t = 3.511) an indicator of the relevance of the given variable as one of the significant outcomes. The mediation test, further, gives support to the fact that Student Engagement mediates the relationship between Generative AI Literacy and Academic Performance (β = 0.108, t = 3.303, p = 0.001). By this it implies that students can acquire skills through AI literacy in two sense, one the direct way and the less obvious one, which is that students are engaged more through AI literacy and therefore, do better in their learning. Having the R^2 value equal to 0.386 on the Academic Performance, the model can be said to possess a moderate predictive ability in the area of research in education.

4.6 Structural Equation Model

Figure 1 : *Path Relationship Diagram*



The validated structural model is illustrated in Figure 1 and the degree of the causal relationships existing between the constructs indicated. The figure displays the Technical Proficiency, Critical Evaluation, Ethical Awareness, and Creative Application, all of which, as the diagram shows, play an important role in the higher-order construct of Generative AI Literacy, which means the contribution of all of them. The Generative AI Literacy and Student Engagement have a positive relationship, and it is robust, i.e., students with high AI skills are more engaged on a cognitive and behavioral level. The correlation between Student Engagement and Academic Performance, therefore, means that students who are engaged in their studies have higher chances of attaining high academic outcomes. Moreover, the direct correlation between Generative AI Literacy and Academic Performance is also rather significant, and it demonstrates that AI literacy is directly and indirectly related to the student achievement through engagement. The introduction of the mediation path in the model is used to explain graphically how AI literacy may impact on the learning processes which extend beyond the technical use. Basically, Figure 1 is consistent with the theoretical underpinnings of the study and shows how different AI-associated competences can interact to achieve both engagement and academic outcomes in higher education.

Discussion

These results represent a valuable amount of empirical data which supports the proposed relations between Generative AI Literacy, Student Engagement, and Academic Performance, thus contributing to the growing amount of literature concerning AI-powered learning in higher education significantly. The authors discovered that the four dimensions of Generative AI Literacy, including one Technical Proficiency and the second one is Critical Evaluation, the third one is Ethical Awareness, and the fourth one is Creative Application, all had a significant positive influence on the overall level of AI literacy among students, which supports the recent academic perspective that AI competence has numerous aspects and is not limited to technical skills alone (Long and Magerko, 2024; Kasneci et al., 2023; Kong et al., 2023). Indeed, these findings are consistent with the global studies, which emphasized the necessity of students to master AI tools, learn how to be critical of AI-generated content, and be aware of the ethical concerns so that they might become highly knowledgeable in AI within the university community (Holmes, 2024; Bećirović et al., 2025). In addition, Generative AI Literacy proved to be a significant variable that has a positive effect on Academic Performance, which was consistent with the evidence used by the authors stating that AI-literate students receive higher quality of learning, develop greater analytical skills, and achieve better academic results (Bećirović et al., 2025; Wang et al., 2023; Zhang & Chen, 2023). This finding, in turn, aligns with the other studies that have been carried out in Nepal or other analogous developing contexts, students who use AI tools effectively report that their academic self-confidence and learning effectiveness have significantly increased (Ghimire et al., 2024; Adhikari & Pandey, 2025). Therefore, with the gradual introduction of generative AI as a learning device into the arsenal, more literate students appear to be better equipped to leverage the device in the productivity and academic performance improvements. The authors of the study also confirmed that the effect of Student Engagement on the relationship between Academic Performance and AI Literacy was significant. This mediating effect is in line with theoretical concepts that indicate that the engagement is the primary contributor to educational success (Fredricks et al., 2004; Kearsley & Shneiderman, 1998). The recent field of learning-analytics and AI-in-education studies support this opinion as well and add that AI-literate students are more inclined to undertake digital learning, become more cognitively engaged, and remain motivated during academic assignments (Bergdahl et al., 2024; Ezeoguine and Eteng-Uket, 2024; Nguyen et al., 2024). Therefore, interaction is an important behavioral connection via which AI literacy results in improved academic outcomes. As the example of Nepal, where the shift to digital higher education remains ongoing, it has been observed that the AI-driven engagement contributes to addressing the academic needs of the students not just but also creates their learning identities (Ghimire et al., 2024; NAAMII, 2025). These findings are in line with the socio-cognitive paradigms that view self-regulated learning and reflective practice as pathways towards academic achievement (Zimmerman, 1989; Panadero et al., 2023). Students capable of critically assessing outputs of AI, perusing digital resources in an ethical way, and creatively working with AI would appear to have a greater level of self-regulation that will ultimately result in increased involvement and higher academic performance. Moreover, the beneficial effect of engagement as an intermediary is consistent with the global results according to which the use of AI-based learning settings leads to the increased curiosity of students, their readiness to take part, and their ability to learn in-depth, assuming they are AI-literate enough (Zawacki-Richter et al., 2024; Naamati-Schneider and Alt, 2024). The results, when put together, highlight the growing importance of Generative AI Literacy as one of the primary academic skills in tertiary education. It resembles the recent debates in the global studies (Dwivedi et al., 2023; Yusuf et al., 2024; Porayska-Pomsta et al., 2024) according to which this research claims that educational institutions can no longer rely solely on the traditional paradigm of digital literacy. Instead, they must introduce AI-related literacy advancement, both technical and ethical, into curriculum, faculty education and student support systems. The outcomes of the study in the regions like Nepal where the problems are found in the infrastructure delivery and various levels of digital preparedness, underline the significance of systematized AI literacy programs, ethical educational training supervision, and educational changes that additionally stimulate and empower learners to learn. Concisely, the study validates that Generative AI Literacy is simultaneously a determinant of the academic success of the student, as well as it leads to the alteration of the learning experience with the increased level of engagement, which is consistent with the multidimensional nature of AI-enhanced learning (Zawacki-Richter & Jung, 2023; Mah & Groß, 2024; Henadirage & Gunarathne, 2024). When relating these findings with the broader theoretical and contextual models, the current study will be an important contribution to the study of the complex interdependence of AI competencies and educational outcomes in the new higher education systems.

Conclusion and Implications

Conclusion

The study focused on the Generative AI Literacy and postgraduate management and education student Academic Performance, and the relationship between Student Engagement and Generative AI Literacy as a mediating variable was investigated. The study discovered that the four components of Generative AI Literacy- Technical Proficiency, Critical Evaluation, Ethical Awareness, and Creative Application- had a significant contribution to the general AI literacy which in turn had a positive influence on Student Engagement and Academic Performance. That is, learners possessing high AI-related competencies have more opportunities to manage AI-aided learning tasks, analyze AI-produced outputs, and apply generative technology imaginatively and ethically to their scholarly assignments. In addition to that, Student Engagement is also determined to be a partial mediator between AI Literacy and Academic Performance relationship implying that AI-literate students not only acquire knowledge but also become more engaged in learning processes, more persistent, and academically self-regulated. Not only does it support the engagement theories, but it finds them in a shifting digital and AI-driven educational landscape, too. Putting these relationships in higher education in Nepal, the study has indicated that in case universities incorporate the concept of AI to teach and learn, the benefits of the students will rely on their capacity to exploit AI tools so that they can benefit ethically and attentively. Overall, the findings contribute to the accumulating body of evidence in the world on AI literacy turning into a fundamental academic skill that preconditions the success of the student in the technologically sophisticated learning conditions.

Implications

Higher institutions of learning in Nepal must endeavor to embed Generative AI Literacy systematically in the minds of their students as this has been found to enhance academic achievement not just in a direct way, but also through the deeper interaction of students. The universities must initiate AI literacy programs, which are carefully planned, arrange training on the practical application and introduce students to the AI-supported learning activities to enable them to acquire both technical and critical skills. Since Ethical Awareness has proven to be another important parameter, AI ethics topics should be introduced into the curriculum, and the emphasis should be put on the use of responsible and transparent generative tools. Taking into consideration the very crucial role of Student Engagement as an intermediary, educators must develop the learning environments that are not only enriched with AI but are also stimulating active student involvement, collaborative learning, and critical thinking. This may be done through utilizing AI-based formative assessments, intelligent tutoring tools and interactive online platforms that will keep the learners longer engaged. In addition, school administrators should support faculty training in AI-based pedagogue to enable teachers to be endowed with the skills and competencies to guide the learners. At the policy level, it is recommended that the authorities in higher education in Nepal must introduce AI literacy standards as part of the curriculum guidelines, allocate funds on the digital infrastructure, and implement national frameworks to precondition the ethical and inclusive application of AI within various universities. Besides that, it is the duty of the institution to collaborate with the industry and AI organizations to enable the students to access real-life AI applications. Future studies can consider using longitudinal, experimental, or mixed-method studies to unravel the progressive process of AI literacy and assess the long-term effect of AI integration on the performance of learners. In addition, researchers are able to determine educational moderators, including institutional support, technological infrastructure, or discipline-specific variations in order to understand more deeply how the AI literacy is connected to the overall educational ecosystems in Nepal.

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