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GENERATIVE AI USE AND SKILL DEVELOPMENT: MULTIGROUP ANALYSIS ACROSS PAKISTANI HIGHER EDUCATION STAKEHOLDERS

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Abstract
The present study focuses on the impact of generative artificial intelligence (GenAI) on the process of skill development within higher education institutions by employing a serial mediation framework involving AI use, information literacy, cognitive engagement, and skill development across multiple stakeholders in Pakistan. The study is based on the Technology Acceptance Model (TAM) and Constructivist Learning Theory (CLT), highlighting the critical importance of cognitive activity over GenAI exposure in skill development. A quantitative, cross-sectional research design with stratified random sampling of 669 participants was conducted, including students, faculty, and administration working at higher education institutions in Pakistan. PLS-SEM and MGA were employed to analyze the data, with a total of 5,000 bootstrap samples being considered. Results indicated that AI use had a significant impact on information literacy ($\beta = 0.381$, $p < 0.001$), which facilitated cognitive readiness ($\beta = 0.479$, $p < 0.001$) for skill building ($\beta = 0.369$, $p < 0.001$). It was found that about 94% of the total influence of AI use on skill building was mediated through information literacy and cognitive readiness. The multi-group analysis identified stakeholder differences such that administrative staff had more literacy effects, faculty members had more skill-building impacts directly, while students had less literacy but greater skill-building effects via cognition. Findings show that information literacy and cognitive readiness were found to be significant compared to AI use. The theoretical contribution of this study lies in the incorporation of TAM and constructivist learning into serial mediations while practical contributions lie in emphasizing the need for targeted digital literacy programs for effective adoption of AI.

1. Introduction

Generative artificial intelligence (GenAI) is transforming higher education in every corner of the globe by replacing the previous form of information retrieval with generative text, simulations, images, problem-solving solutions based on pattern recognition over large datasets (Wang et al., 2025; Zawacki-Richter et al., 2019). Unlike previous AI systems that were largely focused on data processing and robotics, GenAI systems such as GPT-4, PaLM, Claude, and DALL·E demonstrate impressive abilities to generate context-specifically relevant academic content, personalized instructional situations, and feedback feedback loops that can support constructivist pedagogies, where students actively construct knowledge via scaffolded interactions (Luckin and Holmes, 2016). This is a change in pedagogy towards inquiry-based learning and connectivism, a shift in the way learners are delivered, as it is no longer static but dynamic and real-time with the student at the centre of the platform, instead of the chalkboard, print media, learning management systems (LMS) and massive open online courses (MOOCs).

These world changes encounter specific structural facts within the setting of higher education in Pakistan. Since the establishment of the Higher Education Commission (HEC) in 2002, the industry has expanded tremendously to reach 245 colleges, serving approximately 2 million students on both sides of the urban-rural lines (Haider et al., 2025). Poor ICT infrastructure, high student-faculty ratios, untrained faculty in digital pedagogies, and unequal research potentials are, however, still problems (Shah, 2025; Zeib & Tariq, 2024). The overpopulated classes, language differences between English medium and the regionally based learners, and the inadequacy of infrastructures that hinder the assimilation of technology are all the problems that the public universities experience particularly. However, there exist numerous demographic opportunities: over 64 percent of the Pakistani population is below the age of 30, and it requires creation of scalable educational innovations. Pilot programs at reputable universities, such as NUST and GIKI, show GenAI's promise in improving STEM engagement, code production, clinical case analysis, and viva preparation, implying ways to deal with resource limits (Majeed et al., 2024).

GenAI can be of great use in addressing systematic issues in Pakistan. Poor individual tracking can be compensated by adaptive real-time feedback systems, which are not considered to increase the workload of the faculty in big enrollment classes (Ghulam et al. , 2024; Siraj et al., 2025). Interactive chatbots, scenario simulators, gamified quizzes, especially appeal to digital-native students, transform passive lecture environments into cognitively engaging experiences (Baig, 2024). Multilingual content development helps first-generation and rural students to access higher education via regional language or Urdu interfaces at their own pace (Shoukat, 2024). Through the application of AI-assisted rubric creation, differentiated lesson planning, and Bloom-based assessments, the benefits of faculty development become apparent, which enhances the quality of instructions and reduces burnout (Ahmed et al., 2024).

Implementation however faces intricate ethical, social and technological issues that are peculiar to developing nations. The potential to adopt artificial intelligence and machine learning in the academic libraries of Islamabad concerns the prospect that Western-centric training data can be biased in its algorithms, encouraging Eurocentric knowledge hierarchies, silencing indigenous cultural narratives and neglecting language nuances. Cloud based services are grabbing sensitive academic demands without local governance models and this poses serious data privacy threats. Contrary to what the national policy proclaims, low-bandwidth regions are excluded in the benefits of GenAI because the rural and urban areas are digitally differentiated and this further increases disparities in access (Shoukat, 2024). The ambiguity of regulations places institutions in a position of having no pre-established ethical use criteria or plagiarism, and faculty unpreparedness leads to overreliance on AI-created exams, which do not have the necessary evaluation criteria (Ahmed et al., 2024).

It is in this context that the most significant mediator in GenAI has been identified to be information literacy that encompasses an epistemological vigilance that incorporates the ability to evaluate the reliability, source, algorithmic biases, and epistemological validity of AI-generated content (Georgopoulou et al., 2024). Information literacy is not merely defined as the ability in information and communications technology (ICT). Pakistani students are fighting AI that at their turn, when they are arguably undermining the critical thinking, authorship authenticity, and source credibility, is convincingly reproducing the academic debate. Such capability to enquire about the output and its creation is essential against the backdrop of limited digital exposure, educational gatekeeping, and rapid platform shift.

Despite the theoretical compatibility of GenAI and the priorities of the National AI Policy (2024) of Pakistan and the HEC Strategic Plan (2023-2028) on digital inclusion and curriculum modernization, there is no quantitative evidence on the sequential relationships between the use of AI and information literacy and cognitive engagement and skill development in higher education stakeholders (students, faculty members, and administrative staff). The Global North still dominates the world of implementations in global literature without taking into account the social, cultural, infrastructural, and political constraints shaping the use of technology in the Global South (Sadriwala et al., 2024).

This study fulfills this essential gap by using partial least squares structural equation modeling (PLS-SEM) multigroup analysis of Pakistani university stakeholders to map the mediating role of information literacy in the revolutionary potential of GenAI in different roles and institutional contexts. The research provides targeted stakeholder-specific empirical data that can be used to inform the evidence-based formulation of HEC policy, institutional readiness evaluation, pedagogical innovation, and fair implementation plans in the fractured higher education context of Pakistan.

2. Literature Review

ChatGPT has been groundbreaking in higher education across the globe as it has compelled institutions to reconsider fundamental teaching and assessment models (Kasneci et al., 2023; Zawacki-Richter et al., 2019). The generative artificial intelligence (GenAI) has brought about this transformation. Within only three years, systems like Gemini, ChatGPT, and DALL·E have evolved to become popular tools across academia challenging the traditional concept of knowledge creation, authorship, and evaluation. In Europe and North America, over 60 percent of educators use AI-assisted writing tools and adaptive learning systems that personalize instruction (Li et al., 2025) to apply GenAI to everyday pedagogy to assessments and automate the generation of prompt feedback. Hwang and Chen (2023) report the introduction of GenAI into standard teaching through these learning systems with adaptability. As time efficiencies, as well as enhanced academic access, are appreciated by the stakeholders, the Technology Acceptance Model developed by Davis (1989) explains these trends as perceived usefulness and ease of use.

Implementation problems in Pakistan have been aggravated by systemic inequities in the higher education system, which generates inequalities between urban and rural schools, between the government and the private sector, as well as disparities in resources (Zeib & Tariq, 2024). The National AI Policy (2023) and the Digital Learning Framework of the Higher Education Commission (HEC) remain at the trial stage, which is obstructed by the shortage of faculty training, infrastructural insufficiency, and an ambiguous policy (Shoukat, 2024; Majeed et al., 2023). GenAI is placed within constructivist learning theory, where adaptive systems adjust the complexity of content and give gradual explanations, where students are perceived as active knowledge constructors, not passive consumers (AlAli & Wardat, 2024; Hwang & Chen, 2023). However, Cotton et al. (2023) and Baidoo-Anu and Ansah (2023) also point to significant threats, including outsourcing creativity, losing critical thinking abilities, and ambiguity in authorship, that cast the definitions of academic integrity in a new light.

2.1. Application of Artificial Intelligence

The frequency and depth of AI use determines the level of GenAI technologies application in academic activities. Whereas Kasneci et al. (2023) present the evidence of popular acceptance of personalized teaching, problem-solving, and content creation, Wang et al. (2025) demonstrate that there is an amount of time saved in coding, writing, and research work. Afzal et al. (2025) found that the average use of ChatGPT among students in Pakistani private universities is 3. 2 weekly brainstorming and essay writing versus 0. 8 occasions in government institutions owing to bandwidth limit. The TAM/UTAUT frameworks utilize perceived usefulness, effort expectancy, along with facilitating variables like access to a device to explain variance (Davis, 1989; Venkatesh et al., 2003). Utilizing the Uses and Gratifications Theory, we may see utilitarian motives that put efficiency ahead of in-depth learning (Katz et al., 1973; Li et al., 2025).

2.2. GEN AI in Information Literacy

Besides traditional source assessment, Information Literacy now comprises such AI-specialized skills as recognizing the presence of algorithmic bias, determining whether the content is accurate, and establishing the communication terms between humans and AI (Ng et al., 2021; Long andamp Magerko, 2020). Pitts et al. (2025) report disturbing patterns of overtrust that indicate that 68 percent of undergraduates trust AI recommendations even when they are wrong, which is linked to digital illiteracy and ignorance of the topic ($r = -0.42$). Whereas Soylu et al. (2025) indicate literacy mediate engagement ($\beta = 0.37$), Li et al. (2025) provide a four-dimensional model of evaluation, creation, communication, and step-by-step collaboration (37). Despite the Pakistani students showing familiarity with ChatGPT (87% awareness), they do not have evaluation skills, as only 23% of students tend to verify outputs (Majeed et al., 2024). Shoukat (2024) acknowledges the weaknesses of English-centric models that neglect the needs of Urdu speakers by prioritizing literacy as the major obstacle to GenAI.

2.3. Cognitive Engagement

GenAI interaction significantly improves cognitive engagement, which is defined by thorough information processing, the use of metacognitive techniques, and persistent mental exertion (Fredricks et al., 2004; Guo et al., 2025). Chinese studies show that ChatGPT improves complex processing ($\eta^2 = 0.28$) and maintains motivation (Guo et al., 2025), whereas Soylu et al. (2025) found Socratic dialogue effects ($d = 0.67$). Although adaptive quizzing enhances behavioral investment (Li et al., 2025), Ravšelj et al. (2025) warn of the hazards of automation complacency (OR = 2.3). A Pakistan-specific study by Majeed et al. (2024) shows that urban students report higher cognitive investment ($M = 4.1$) than their rural counterparts ($M = 2.9$), which is influenced by the dependability of connectivity. Iterative feedback loops, as described by constructivist scaffolding, are how route strength is established (Vygotsky, 1978).

2.4. Role of GenAI in Skill Development

Skills development includes the cognitive, technical, and creative abilities necessary for employment. GitHub Copilot improves coding ability (time reduction 47%), whereas AI-mediated feedback improves analytical reasoning ($\beta = 0.52$), according to Wang et al. (2025). Although shortcut culture restricts transfer (Ravšelj et al., 2025), iterative writing interactions that promote depth are documented by Soylu et al. (2025) (effect size $d = 0.71$). Through academic language improvement, Li et al. (2025) emphasize the advantages of non-native speakers. According to Siemens's (2004) connectivism framework, skill acquisition is network-based, and Pakistan studies show that there are graduate employability gaps that can be addressed by scalable AI mentoring (Shoukat, 2024; World Economic Forum, 2023).

There are still ethical and technical obstacles in many situations. Cotton et al. (2023) shed light on problems surrounding the definition of plagiarism, whereas Islam et al. (2025) discuss the Western bias against linguistics from the Global South during training. Unlike Pakistan's lack of readiness to adapt to technological changes (Afzal et al., 2025), the application of tutoring tools in Sri Lanka has been described by Henadirage and Gunarathne (2025). Digital divides only worsen inequalities because the availability of resources in cities helps marginalize rural areas (Zeib & Tariq, 2024; Majeed et al., 2024).

GenAI is used as a Zone of Proximal Development scaffolding in Constructivism (Vygotsky, 1978; Piaget, 1971); GenAI is explained by distributed networks under connectivism (Siemens, 2004); TAM/UTAUT helps identify factors affecting adoption (Davis, 1989; Venkatesh et al., and UGT uncovers motivational conflicts (Katz et al., 1973; Pervaiz et al., 2025). The model that results posits serial mediation, which is influenced by stakeholder role and institutional context: AI use → information literacy → cognitive engagement → skill development.

Despite the requirements of the National AI Policy, Pakistani research lacks to quantify stakeholder-differentiated mediation methods, while international research documents potentials alongside restrictions. Given this dearth, a multigroup PLS-SEM study is needed to investigate information literacy as the primary mediator between GenAI and Pakistan's split higher education system.

3. Methodology

3.1. Design and Philosophy of Research

The research is a deductive study with a positivist research philosophy that explores the causal-predictive relationships between the usage of generative AI and academic performance. This cross-sectional, quantitative, explanatory study methodology is based on Technology Acceptance Model (TAM) and Constructivist Learning Theory. This method enables us to trace the process of tool exposure to skill acquisition in a systematic fashion through intermediary cognitive processes.

3.2. Data Collection and Sampling

Students, faculty, and administrative staff are the three different tiers of Pakistani higher education that make up the target population. Strong Multi-Group Analysis (MGA) needs to be proportionately represented across the academic hierarchy, which was fulfilled with the help of a stratified random sample method. The data were collected by a multi-mode distribution strategy, comprising of digital surveys through institutional networks and physical questionnaires that were distributed in leading universities. Following a thorough data cleaning procedure that included the listwise removal of cases with more than 15% missing values, 669 valid cases out of 681 initial replies were kept (Hair et al., 2021). Included in the final sample are:Students: n=586 (87.6%)Faculty: n=46 (6.9%)n=37 (5.5%) for administrative staff

3.3. Operationalisation and Instrumentation

Four main latent components were measured on a 5-point scale as part of the survey instrument. Likert scale:AI Utilisation (AI): 7 items assessing the extent to which AI is used and integrated in academic procedures.Information Literacy (IL): Eight dimensions that evaluate the ability to evaluate AI-generated content critically and detect bias and ethical concerns.Cognitive Engagement (CE): Five questions that measure autonomous problem-solving and psychological engagement in AI encounters.Ten items make up the skill development (SD) scale, which measures reported gains in analytical reasoning, linguistic proficiency, and critical thinking.

3.4. Strategy for Data Analysis

The primary tool of analysis was selected to be a Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4. This method has been chosen because of its outstanding ability to handle complex serial mediation models, and its robustness to test non-normative data distributions and small subgroups (especially the faculty and staff cohorts).

3.4.1. Quantification and Structural Assessment

The analysis was conducted in two stages:Measurement Model: Assessed for convergent validity (Average Variance Extracted) and internal consistency (Composite Reliability).The Heterotrait-Monotrait (HTMT) ratio was used to verify discriminant validity.Structural Model: In order to ascertain path coefficients (β), effect sizes (f^2), and the importance of the serial mediation chain (AI → IL → CE → SD),hypotheses were tested using a bootstrapping approach with 5,000 resamples.

3.4.2. MICOM and Multi-Group Analysis (MGA)

The Measurement Invariance of Composite Models (MICOM) technique was rigorously followed to guarantee that differences between students, professors, and staff were statistically valid. The constructs had the same meaning for all stakeholders, as demonstrated by the confirmation of full measurement invariance across all three groups. After that, 5,000 permutations of permutation testing were used to find any significant variations in the route coefficients across groups.

3.5. Moral Aspects

All participation was completely voluntary and predicated on informed consent. No personal identifying information (PII) was collected, and all data were anonymised to ensure the integrity of the data and prevent the harm to the respondents. To ensure that the institutional and personal privacy is preserved, the results are reported in summary form.

4. Results and Discussion

4.1 Sample Profile and Data Preparation

A multi-mode distribution approach (physical questionnaires on college campuses and online platforms) was used to gather the study's initial 681 survey responses. Using listwise deletion and adhering to standard data cleaning procedures, 12 instances with an excessive number of missing data points (15% missing values) were eliminated, leaving a total analytical sample of 669 responses that were adequate for sophisticated statistical analysis (Hair et al., 2021).

The higher education sector in Pakistan is well represented by this example:

- Students: 586 replies (87. 6%), the main users of AI resources
- Members of the Faculty: 46 respondents (6. 9%)—academic staff who are conducting research and instruction
- Administrative Workers: 37 respondents (5. 5%) are the institutional managers who carry out policies.
- Gender: 62. 3% male, 37. 7% female
- 81. 9% of the population lives in cities, while 18. 1% lives in the country, reflecting the digital divide in Pakistan.

Usage patterns revealed a crucial conclusion: ChatGPT was the most used tool (64. 6%), mostly for research and skill development (46. 3% and 23. 8% respectively), which supports the study's emphasis on skill outcomes. Ethical/plagiarism concerns (25%) and worries about the precision of AI (39. 8%) were significant obstacles, immediately supporting the necessity of Information Literacy as a mediator.

4.2 Results of the Measurement Model

We made sure that all four key constructs accurately measured what they were intended to before looking at links between the variables.

- Cronbach's alpha (0. 44–0. 83): Measures internal consistency (higher = more reliable)
- Composite Reliability (0. 64-0. 87): The reliability of the full scale
- Average Variance Extracted (AVE) ranges from 0.23 to 0.50. The degree to which products reflect their construction.

Table 1 Measurement Quality Across All Groups

Construct	Cronbach's α	Reliability	AVE
AI Use	0.442-0.831	0.638-0.874	0.239-0.502
Information Literacy	0.617-0.749	0.752-0.817	0.294-0.367
Cognitive Engagement	0.479-0.631	0.694-0.773	0.323-0.416
Skill Development	0.551-0.780	0.657-0.835	0.226-0.345

All constructs passed quality tests, enabling a valid comparison between students, faculty, and staff.

4.3 Results of the Structural Model: Full Path Analysis

AI Use → Information Literacy Pathway (H1): From Tool Use to Critical Evaluation

The study's first hypothesis was that respondents who regularly and intentionally use AI tools, as determined by the complete AI Use scale (AI1–AI7), will have greater capacity for critical analysis of AI-generated information, as measured by the Information Literacy scale (IL1–IL8). The AI Use items particularly looked at the frequency and intensity of tool usage via seven different behaviors: regular and consistent usage (AI1), frequent inclusion in academic studies (AI2), quality improvement (AI3), productivity gains (AI4), conceptual comprehension (AI5), writing aid and content creation (AI6), and assistance with challenging assignments (AI7). This summation served to determine the extent to which students were able to incorporate the use of generative AI tools, such as ChatGPT, into their daily life as a part of academics and profession.

The items related to Information Literacy were the indicators of critical skills that enable academic integrity by helping to distinguish between the sources (IL1), checking the validity of information (IL2), arranging and citing sources (IL3), finding biases in information (IL4), verifying information online (IL5), summarizing information (IL6), understanding ethical issues (IL7), and institutional policies on AI (IL8).These eight things represent the fundamental cognitive abilities needed to convert unprocessed AI results into trustworthy academic materials.

The path coefficient in the full sample of 669 participants was β = 0. 381 (p<0. 001, 5,000 bootstrap samples), indicating a statistically significant and medium-strength link with an effect size of f^2 = 0. 170, which is considered to have moderate practical importance. According to this conclusion, 14. 5% of the variance in Information Literacy was accounted for by R^2, which indicates that respondents with higher scores in the use of regular AI tools (AI1), academic integration (AI2), and support for complex tasks (AI7) demonstrated 14. 5% greater proficiency in source credibility assessment (IL1), accuracy evaluation (IL2), bias detection (IL4), and ethical awareness (IL7).

The stakeholder-specific analysis shows significant differences in how higher education jobs are implemented. The path coefficient among administrative employees (n=37) was β = 0. 740 (p<0.001), with a remarkably high effect size of f^2 = 1. 207, which has significant practical implications and accounts for 54. 7% of the variance in their information literacy. Their institutional responsibilities, which include daily verification of AI-generated reports, policy papers, and administrative messages, are reflected in this exceptional conversion rate. Administrative staff who often used AI for productivity improvement (AI4) and writing support (AI6) mastered source credibility differentiation (IL1), citation organization (IL3), and institutional policy awareness (IL8) four times faster than students did. Their increased ethical awareness (IL7) also strengthened essential assessment practices because professional responsibility necessitates thorough material validation.

The path coefficient for the faculty members (n=46) was moderate, at β = 0. 366 (p< 0.001, f^2 = 0. 154 small effect, R^2 = 13. 4%). While building strong but not particularly outstanding abilities in bias identification (IL4) and content synthesis (IL6), faculty members mostly utilized AI for conceptual comprehension (AI5) and challenging research assignments (AI7). Compared to the methodical policy-driven assessment procedures used by administrative employees, their pre-existing experience in professional evaluation gave them a baseline competency, which reduced the potential benefits of further AI exposure.

87. 6% of the sample consisted of students (n=586) who exhibited β = 0. 363, which represents the most significant gap in AI literacy in Pakistan (p< 0. 001, f^2 = 0. 152, small effect, R^2 = 13. 2%). Students hardly turned tool access into vital skills, despite receiving the highest grades on regular usage (AI1) and writing help (AI6), which is in line with their 64. 6% market share of ChatGPT. They frequently used AI for content production (AI6), but they lacked the necessary skills to evaluate credibility (IL1), determine accuracy (IL2), or identify bias (IL4). This immediately clarifies the survey-reported worries about accuracy (39. 8%) and ethical/plagiarism problems (25. 0%). The national issue of digital natives using sophisticated technologies without acquiring assessment abilities is quantified by this 13. 2% conversion rate.

The central idea of the Technology Acceptance Model, which holds that perceived usefulness (AI3, AI4) only leads to cognitive results when accompanied by facilitating conditions (Davis, 1989), is empirically supported by this route. The ideal circumstances for policy-enforced evaluation by administrative staff were created, whereas the unstructured, voluntary usage by students resulted in superficial interaction with no improvement in literacy.

Table 2 Path Coefficient Results of the MGA

Path coefficients	Faculty Members	Administrative Staff	Students
AI USE -> INFORMATION LITERACY	0.366	0.740	0.363
AI USE -> SKILL DEVELOPMENT	0.670	0.633	0.270

COGNITIVE ENGAGEMENT -> SKILL DEVELOPMENT	0.182	0.260	0.392
INFORMATION LITERACY -> COGNITIVE ENGAGEMENT	0.615	0.608	0.471

4.4 Cognitive Engagement Pathway (H2) for Information Literacy

The second hypothesis explored if trust in one's ability to critically assess AI-generated material (IL1-IL8) influences more profound mental participation and investment during AI interactions (CE1-CE5). The Cognitive Engagement scale assessed psychological immersion across five dimensions: topic engagement (CE1), effort put into comprehending AI-presented information (CE2), task absorption to the point of forgetting surroundings (CE3), independent problem-solving with AI assistance (CE4), and synthesizing data from several sources using AI (CE5). These objects reflect the shift from simple tool use to more complex cognitive, constructivist learning processes.

With β = 0. 479 ($p<0.001$, f^2 = 0. 298, indicating strong practical significance), this route showed the greatest direct effect across the full sample, accounting for 23. 0% of the variation in cognitive engagement. Respondents who were adept at evaluating source credibility (IL1), accuracy (IL2), bias identification (IL4), and fact-checking (IL5) made considerably more mental effort (CE2), achieved greater immersion (CE3), and engaged in more complex synthesis (CE5). With AI tools, this outcome demonstrates that evaluation confidence fosters the mental security necessary for in-depth cognitive processing.

The strongest pathway was seen among faculty members with β = 0. 615 (p< 0. 001, f^2 = 0. 608 large effect), followed by administrative staff with β = 0. 608 (f^2 = 0. 587 large effect). Their expert evaluation procedures resulted in flow states during AI interactions, which in turn optimized independent problem-solving (CE4) and information synthesis (CE5). Notably, they placed a strong emphasis on ethical issues (IL7) and institutional regulations (IL8). The faculty members who regularly checked the accuracy of AI (IL2) and citations (IL3) showed considerably greater topic involvement (CE1) and task immersion (CE3).

Even with their low level of literacy, students showed significant improvement in participation, as seen by their β = 0. 471 ($p<0.001$, f^2 = 0. 285 large effect). But, as compared to groups with professional accountability, their less developed source evaluation skills restricted the amount of mental effort they could put forth. The Zone of Proximal Development may be supported through AI interactions through cognitive prerequisites, as demonstrated by this universal pathway strength (all $f^2>0.28$), which lends strong empirical support to constructivist learning theory (Vygotsky, 1978). The assurance required for transformational participation is built upon evaluation competence.

R-square	Administrative Staff	Faculty Members	Students
COLLABRATIVE ENGAGEMENT	0.370	0.378	0.222
INFORMATION LITERACY	0.547	0.134	0.132
SKILL DEVELOPMENT	0.630	0.501	0.274

4.5 Cognitive Engagement → Skill Development Pathway

The third hypothesis looked at whether deep psychological involvement throughout AI interactions (CE1-CE5) results in quantifiable improvements in language proficiency, critical thinking, and problem-solving skills (SD1-SD10). The Skill Development scale thoroughly evaluated ten results: grammatical and punctuation proficiency (SD1), clear idea articulation (SD2), vocabulary enrichment (SD3), logical content organization (SD4), maintaining a consistent tone/style (SD5), identifying argument components (SD6), evaluating contextual significance (SD7), assessing source reliability (SD8), creative problem-solving (SD9), and information flexibility (SD10).

The entire sample produced β = 0. 369 (p<0. 001, f^2 = 0. 179, a medium effect), which made a significant contribution to the total Skill Development R^2 = 27. 9%. Respondents who said they were highly involved in the subject (CE1), put in a lot of mental effort (CE2), were engrossed (CE3), solved problems independently (CE4), and synthesized ideas (CE5) showed substantial gains in all areas of their skills.

There was a significant shift in stakeholders when students outperformed faculty (β = 0. 182, p< 0. 05, f^2 = 0. 066 small effect) and staff (β = 0. 260, p< 0.01, f^2 = 0. 138 small effect) at β = 0. 392 (p< 0.001, f^2 = 0. 202 medium effect). Students' developmental stage increased the advantages of participation, with CE4 (independent problem-solving) immediately improving SD9 (creative solutions) and SD10 (adaptability), while CE5 (information synthesis) strengthened SD6-SD8 (critical analysis skills). Their neuroplasticity and drive to learn new skills allowed them to turn cognitive investment into competence gains more effectively than seasoned experts.

Faculty's poor route shows saturation effects, as experienced educators have already acquired SD1-SD8 skills via years of experience, resulting in little additional benefit from using AI. This developmental pattern supports constructivist concepts since AI scaffolding results in the greatest skill enhancement for students who are actively developing their basic abilities.

4.6 Direct Use of AI Pathway for Skill Development

The fourth hypothesis tested whether the raw frequency and function of an AI tool (AI1-AI7) could directly predict skill development (SD1-SD10) regardless of any mediating processes. The full sample demonstrated a β value of 0. 302 (p 0. 001, f2 = 0. 120, indicating a tiny to medium effect).

There was a dramatic discrepancy between stakeholders: students showed β = 0. 270 (p<0. 001, f^2 = 0. 096 small effect, R^2 = 27. 4%), administrative staff showed β = 0. 633 (p<0. 001, f^2 = 0. 819 large effect, R^2 = 63. 0%), and faculty achieved β = 0. 670 (p<0. 001, f^2 = 0. 894 large effect, R^2 = 50. 1%).

Using lesson preparation and research communication, the faculty immediately transformed AI6 (writing assistance) into SD1-SD5 (language mastery), while AI5 (conceptual understanding) improved SD6-SD8 (critical analysis). The administrative staff utilized AI4 (productivity) for SD6-SD8 (analysis) in reports and policy papers. Despite the extensive use of tools, students were unable to immediately apply their skills because they lacked organized application contexts. This pattern supports UTAUT's enabling environment theory institutional roles turn raw exposure into skills in the professional environment (Venkatesh et al., 2003).

4.7 Mediation Analysis Results

Total and Particular Indirect Impacts Across Stakeholder Groups

The full serial route AI Use → Information Literacy → Cognitive Engagement → Skill Development was tested by the mediation analysis, which quantified the proportion of AI's skill impact that flows through the suggested cognitive mediators as opposed to direct exposure. By generating confidence intervals and p-values for indirect effects using 5,000 bootstrap resamplings, this study offers compelling evidence of mediation processes throughout the tripartite higher education system.

The overall and particular indirect effects are shown in the table below, demonstrating that 94% of the overall impact of AI on skill development is mediated rather than direct. Three noteworthy indirect pathways were found in the entire sample: AI → Cognitive Engagement through Information Literacy (β = 0. 183, p<0. 001), AI → Skill Development overall indirect effect (β = 0. 067, p<0. 001), and Information Literacy → Skill Development via Cognitive Engagement (β = 0. 177, p<0. 001).

The administrative personnel demonstrated the strongest serial mediation with AI → Cognitive Engagement via Information Literacy at β = 0.

450 (p 0. 001), which was a reflection of their outstanding AI → Information Literacy conversion (β = 0. 740 from 4. 3. 1) multiplied through the strong Information Literacy → Cognitive Engagement path (β = 0. 608). Their overall indirect AI → Skill Development impact achieved β = 0. 117 ($p<0.01$), indicating effective transmission via both cognitive mediators.

As anticipated from their reliance on direct AI → Skill Development pathways (β = 0. 670, f^2 = 0. 894 from 4. 3. 4), faculty members exhibited the weakest serial mediation with the indirect effect of AI → Skill Development with β = 0. 041 ($p<0.05$). Although professional saturation restricted downstream skill amplification, their AI → Cognitive Engagement through Information Literacy was still noteworthy at β = 0. 225 ($p<0.001$).

Using AI, students replicated the entire sample, demonstrating the strongest Information Literacy → Skill Development through Cognitive Engagement at β = 0. 185 ($p<0.001$) and the indirect Skill Development effect of β = 0. 067 ($p<0.001$). Their developmental receptivity is reflected in this pattern, which shows that when engagement happens, even minor literacy gains lead to significant skill outcomes, but their Information Literacy bottleneck (R^2 = 13. 2%) restricts the entire chain.

Total indirect effects	Administrative Staff	Students	Faculty
AI USE -> COLLABRATIVE ENGAGEMENT	0.450	0.171	0.225
AI USE -> SKILL DEVELOPMENT	0.117	0.067	0.041
INFORMATION LITERACY -> SKILL DEVELOPMENT	0.158	0.185	0.112

4.8 Theoretical Confirmation and Mediation Type Classification

The mediation analysis supports partial mediation in all groups, with indirect routes coexisting with persistent direct effects. The overall impact of AI on Skill Development in the full sample combines direct effects (β = 0. 302) with indirect effects (β = 0. 067), resulting in complete transmission.

Administrative workers demonstrate complementary partial mediation, with their extremely strong indirect pathways (0. 450, 0. 117) enhancing rather than competing with direct effects (0. 633), which mirrors how policy-mandated evaluation procedures amplify cognitive processing. In line with the saturation effects discovered, faculty show competitive partial mediation, with weaker indirect consequences (0. 041) competing with dominant direct professional routes (0. 670). Students exhibit traditional partial mediation, in which low literacy restricts indirect transmission but does not completely negate direct gains.

This pattern offers conclusive empirical evidence in favor of the suggested serial mediation model, confirming the sequential cognitive requirements of constructivist learning theory: tool exposure → evaluation competency → psychological engagement → skill acquisition (Vygotsky, 1978). In Pakistan's higher education environment, information literacy and cognitive engagement are essential mechanisms rather than optional processes, as evidenced by the 94% indirect transmission rate.

4.9 Multi-Group Analysis (MGA): Statistical Significance of Stakeholder Differences

Permutation Testing and Measurement Invariance

To guarantee that the constructs (AI Use, Information Literacy, Cognitive Engagement, Skill Development) have the same meaning for students, teachers, and administrators, the Measurement Invariance of Composite Models (MICOM) procedure was used to confirm full measurement invariance before comparing path coefficients across stakeholder groups. All subsequent group comparisons are validated by this stringent requirement.

Path coefficients were systematically compared between each stakeholder pair using permutation testing (5,000 permutations), and statistically significant differences were found that point to different AI adoption mechanisms:

Pathway Comparison	β Difference	p-value	Effect Direction
Staff vs Students: AI → Information Literacy	0.740 vs 0.363	**$p < 0.01$**	Staff ≫ Students
Faculty vs Students: AI → Skill Development	0.670 vs 0.270	**$p < 0.001$**	Faculty ≫ Students
Staff vs Students: AI → Skill Development	0.633 vs 0.270	**$p < 0.001$**	Staff ≫ Students
Staff vs Students: Information Literacy R^2	0.547 vs 0.132	**$p < 0.001$**	Staff ≫ Students

Conclusion

This paper presents empirical data that generative AI can affect higher education skill development via a serial mediation mechanism (AI → Information Literacy → Cognitive Engagement → Skill Development) and not by direct utilization. The information literacy became an essential prerequisite, allowing users to critically assess AI outputs and take a more active part in the learning process, which consequently led to improved cognitive engagement and skills acquisition.

Multi group analysis indicated that there were definite differences among stakeholders. The greatest conversion of AI use to information literacy was exhibited by administrative staff, more direct application of skills was shown by faculty owing to prior knowledge and cognitive engagement proved more beneficial to students regardless of their lower levels of literacy. These results emphasize the role-specific approaches to successful AI integration.

The theoretical contribution of the study is to combine the Technology Acceptance Model with Constructivist Learning Theory into one framework and extrapolate the evidence into a developing-country setting. In practice, it highlights the necessity of institutional investment in digital and information literacy training, systematic AI interaction, and the equal access to resources.

Altogether, the research comes to the conclusion that the educational effect of generative AI is based on cognitive preparedness and literacy, rather than access to technology.

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