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Impact of generative artificial intelligence in education: Opportunities, challenges, and strategies

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Abstract

Due to the exponential growth of generative artificial intelligence (GenAI) technologies, especially large language models, like ChatGPT, Claude, and Gemini, unprecedented shifts in education have occurred in nearly every part of the world. Although adoption rates have risen exponentially. It has been demonstrated that a fifth of these technologies bear extensive and diverse implications on the efficiency of teaching and learning, academic honesty, and the attainment of learning outcomes. The present study concerns three core issues: to begin with, the empirical models used to assess the GenAI, and its difference effects in educational settings are nonexistent; secondly, there is a lack of insight into the implementation-based strategies to maintain the balance between innovation and academic integrity; and finally, the policies within the measurement of equitable access and ethical practices lack empirical justification. A mixed-methods design with educational institutions based in various countries, as well as qualitative, GenAI implementation frameworks was used. Evidence shows that GenAI integration is significantly associated with better personalized learning improvements ($\beta = 0.67$, $p < 0.001$) and increased pedagogical efficiency (42% of administrative tasks were reduced), but at the same time, it is associated with significant issues, such as academic dishonesty (88% of students used GenAI to complete assessments) and equity (equity). The analysis has identified five key success factors in the success of GenAI implementation that are extensive faculty training programs, strong ethical guidelines, dynamic assessment practices, technology support, and alignment among policies.

Keywords: Generative artificial intelligence, Education, Large language models, Academic integrity, Pedagogy, Digital transformation.

1. Introduction

The development of generative artificial intelligence is a provisional change in the field of educational technology significantly changing the sphere of teaching, learning, and assessment in ways that have never been seen before. With ChatGPT publicly released in November, 2022 education institutions all around the world have seen an unprecedented rise in the use of AI and latest empirical research evidence suggests an increase in both university students using AI GenAI has risen dramatically, with 66 percent of students using AI in early 2024 to 92 percent in late 2024, constituting one of the fastest curves in technology adoption in education history [1,2]. This is not just a question of technological novelty but this is also the redefinition of pedagogical relations, process of knowledge construction and even ontology of the process of learning itself.

The capabilities of large language models (such as ChatGPT (OpenAI), Claude (Anthropic), Gemini (Google), and their offshoots) are natural language understanding, natural language generation, and contextual reasoning abilities, many times greater than any previous educational technologies could achieve. Such systems show astonishing skill on a variety of cognitive activities such as essay writing, problem-solving, code writing, language translation, and creative ideation and are virtually available

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intellectual tutors both to students and teachers. Their deep learning characteristics, where the models are trained on large corpora (billions of parameters) makes it possible to have a delicate type of conversation, offer personal explanations, create educational content and aid with intricate analytical objectives that were previously thought to solely exist as a part of the cognitive realms of humans.

The educational implications of this technological revolution are far-reaching and they include not only the opportunities of revolution but also the challenges that one may face [3-5]. GenAI technologies on one hand have unparalleled opportunities to democratize the access to personalized learning, anomorphize individualized teaching, cut down the work of educators, improve student interaction, and make new pedagogies possible. Based on recent examples, the study has shown that teachers who use GenAI systems state that their productivity improvements have been considerable, with 42% of them reporting a lower administrative load, 25% of them reporting higher levels of customized learning features, and 18% of them reporting higher rates of student engagement. Also, GenAI facilitates the achievement of traditional educational aspirations like the adaptive learning paths, instantaneous formative responses and unrestricted access to expert-style tutoring services.

On the other hand, GenAI technologies have rapidly spread, which has led to unprecedented the disruption of traditional education systems, specifically academic honesty, equitable opportunity, pedagogical authenticity, and the inculcation of critical thinking skills [1,3]. The current statistics indicate that 88 percent of learners have used GenAI tools to complete their assessments, of which 58 percent confessed to using those technologies in a manner that is considered illegal by institutional rules as academic dishonesty. Besides, professors involved in various research works are quite concerned about the fact that GenAI may hurt the development of key skills, promote unhealthy reliance on technology, promote plagiarism, support any form of algorithmic biases, threaten data privacy and promote disparities in education in existing inequalities. The complexity of these issues is further complicated by the lack of transparency in the decision-making of the AI, the excessive dynamism of the properties before the policy can be formulated, the underlying and inherent tension between the promotion of the use of innovative tools and the maintenance of academic quality.

The contemporary education ecosystem is at an acute crossroad where the use of GenAI is widespread with little to no signs of institutional framework or empirically proven pedagogical approaches, or institutional policy direction [1,6]. Even educational institutions around the world are struggling with the major issues How do teachers develop tests that will actually assess the learning of students during a period when AI is capable of producing advanced responses in real-time? How can the capabilities of GenAI be used through pedagogical methods and approaches that support instead of reduce critical thinking? What still needs to be done is how institutions can guarantee equal access to AI technologies and avoid development of new digital divides. How should AI application to education be regulated? What does this mean regarding the preservation or conceptual redefinition of academic integrity in regard to these technological possibilities?

These are questions that are not technical and administrative questions, but go to the very root of the purpose and methods of education, which are philosophical. The introduction of GenAI is confronting the classical ideas of the authorship, originality, intellectual work, and even what learning is. It drives teachers to reevaluate not only which skills and capabilities are the most valued in an AI-enhanced world, but also how learning will be evaluated in a world where AI support is everywhere and what the best pedagogical strategies ought to do in helping learners be better prepared to live in a world where human-AI collaboration will be the order of the day. In addition, the universal characteristic of the GenAI implementation need to consider all cross-cultural differences on educational values, technology infrastructure, regulations, and methods of implementation.

The importance of learning about the educational effect of GenAI is not only confined to the impact on the classroom environment but is far-reaching to the rest of society [2,6]. Education is the main tool that can be used in the development of workforce, social mobility and human capital. The manner in which educational organizations negotiate through the GenAI revolution will, therefore, have a far-reaching impact on the economic viability, social justice, democratic, and human prosperity in future. The level of stakes is truly immense: a well-integrated GenAI can democratic access to high-quality education in the world, as it might lead to increased inequality of education and deterioration of learning standards as well as to the inability of students to become the artists of the technological age.

The emergence of GenAI in education has become a widespread trend in recent academic literature, and in two years since the release of ChatGPT, it has already grown to thousands of publications. Nonetheless, this growing literature has serious shortcomings and weaknesses that are taken care of by this research. First, the available literature is mostly comprised of conceptual treads, opinion articles, and small-level qualitative research, and there are no large-scale empirical studies that can produce evidence with substantial strength regarding the actual effects of GenAI on learning outcomes, pedagogical nature, and change of institutions. Second, much of the contemporary studies is very limited to exclusive perspectives, including plagiarism detection, or tool abilities without extensive frameworks open to technological, pedagogical, ethical, policy, and sociological considerations. Third, the current literature shares excessive views on North American and European backgrounds, and not enough of the issue is given to the implementation issues and opportunities in various world contexts.

Fourth, the technological advancement has been rather swift, introducing a temporal difference in the world where the results of the research can be based on the outdated performances of AI not considering the progressive increase in its capacities, multiple modalities, and functionality to apply. Fifth, current literature is insufficient to deepen the comprehension of the intersectionality of the GenAI impacts on various educational settings, student bodies, fields of discipline and the type of institution, mostly generalized conclusions which fail to show critical contextualized differences. Sixth, the empirical background is inadequate as far as the effective implementation strategies are concerned and little systematic assessment of alternative policy strategies, pedagogical intervention, or technological setups is presented.

Moreover, the available literature has a significant lack of quantitative rigor of design methods that can give causal associations to and quantify the impact of GenAI interventions. The majority of the studies are based on the descriptive statistics, the survey of attitudes and perceptions, or the theoretical framework that was not empirically validated. Research utilizing the advanced statistical methods such as structural equation modeling, hierarchical regression analysis, propensity score matching, and longitudinal studies is critically warranted to comprehend the multivariate intricacy of GenAI adoption, pedagogical practices, student factors, institutional factors, and outcomes of education.

Also, the emerging scholarship lacks sufficient coverage on the dynamic and changing aspect of GenAI technologies. The research results of 2023 might not be applicable to 2025 with its examples, which were far more competent, and thus a continuous effort of the updated empirical studies is necessary. The literature also does not discuss enough the heterogeneous effects of GenAI on various stakeholder groups (such as differences by the socioeconomic background of students, academic prior performance, technological experience, language and discipline background, etc.). Ability to comprehend these differences impacts is the key in the formulation of equity implementation policies that will increase and not reduce the access to education. Another essential gap is the lack of advanced theoretical frameworks that are specifically meant to be used in learning when it comes to GenAI. Although the researchers have applied the proven models, including Technology Acceptance Model, Diffusion of Innovations Theory, and other learning theories, they were created in other technological contexts and do not necessarily account for the distinctive features of GenAI, including the conversational nature, the seeming cleverness, veiled nature, fast paced evolution, and the tremendous potential it might spread throughout the cognitive and learning processes. There is a need to develop new theoretical perspectives explaining human-AI cognitive alliances, distributed intelligence, and the shift in learning moving towards more knowledge acquisition and less knowledge navigation and synthesis.

Since the existing literature has determinate gaps, in this study the following broad objectives are being sought:

1) To engage in a massive empirical study of GenAI adoption trends, implementation plans, and perceived effects in different educational institutions worldwide which would present quantitative data about prevalence, application setting, and institution reaction.

2) To determine and substantiate a broad theoretical framework on which GenAI multidimensional effects on education can be understood by incorporating the technological, pedagogical, ethical, policy, and sociological approaches into an analytical system.

3) The researcher will use advanced statistical techniques, such as the structural equation modeling and the hierarchical regression analysis to establish the mediating and moderating role of GenAI in influencing pedagogical effectiveness, learning outcomes, academic integrity, and institutional transformation.

4) To extract systematically the issues related to the implementation of GenAI in education, such as the threats to academic integrity, equity, the preparedness of faculty, policy failures, as well as the problem of assessment validity, and evidence-based characterize the scope and severity of these issues.

5) To recognize and assess optimal approaches to responsible GenAI integration that could deliver the greatest educational value and reduce the risks, researching the examples of successful implementation, the policy frameworks, pedagogical innovations, and technological solutions.

6) To examine the differential effects of GenAI in varied educational settings, student groups, and academic fields, with regard to how these effects differ based on such factors as the nature of the institution in which they happen, geographic location, socio-economic status as well as the academic disciplines.

The contributions of the research to the field of educational technology research and practice are several and new:

First, it offers the ample empirical exploration of the effects of the educational impacts of GenAI that has been conducted up to date, utilizing the data of different institutions in various countries and various viewpoints of stakeholders. This is of substantial importance in relation to the past research and allows the statistical analysis of the global trends with considerable force, yet considering regional distinctions. Second, the research constructs and confirms a new theoretical framework of genAI uniquely aimed at analyzing the Educational GenAI Integration Framework (EGIF) the synthesis of the technological affordances, pedagogical, ethical, policy, and socio-cultural dimensions and variables into an analytical viewpoint. This model offers theoretical understanding and analytical format that is currently lacking in the literature.

Third, the study adopts advanced quantitative designs not widely utilized in studies on educational technologies such as structural equation modeling that uses multiple mediators and moderators, hierarchical regression design with cross-level interactions with participatory design, and propensity score matching to build quasi-causal conclusions. The approaches allow pinpointing complicated associations and magnitude of effects with accuracy never before witnessed. Fourth, the research offers practical evidence-based implementation tips of GenAI based upon the systematic research of the successful examples and confirmed by empirical studies. The strategies are responsive to important issues in implementation and are also practical as guides to educators, administrators, and policymakers. Fifth, the study makes methodological novelties such as new measures of GenAI literacy, pedagogical effectiveness in AI-enhanced situations, and institutional preparedness to adopt AI. These tools cover the gaps in existing measuring tools and allow conducting research in the future. Sixth, the results shed bright information on significant heterogeneity of the effects of GenAI across contexts that refutes overgeneralization of claims and offers insightful results about where, how, and who will benefit or be harmed the most by GenAI integration. Such a contextual sensitivity makes the findings more practical. Lastly, the study contributes to the theoretical knowledge of the interaction between humans and AI in the educational context and brings the knowledge that could be utilized in the future beyond practical interests to the global questions of cognition, learning, and knowledge as well as the alteration of education in technologically mediated societies.

2. Methodology

This study used a mixed-method research design that amalgamated both quantitative and qualitative designs to investigate the many-sided influences of generative artificial intelligence in learning activities. The methodological model was designed in such a way that it has managed to fulfill the research objectives in terms of several complementary analytical approaches, which included mass survey research, institutional documents, and expert interview, and sophisticated statistics modeling. The section outlines the research design, data collection methods, data analytical methods and measures that would be undertaken to guarantee validity, reliability, and generality of the results.

2.1 Research design and sampling

Sampling

The sampling has involved purposeful sampling regarding the specific intervention and locations sampled by the research. The research gathered data on faculty members and students at the institutions that participated in the research at the individual level. Faculty participants were sampled in a proportional manner based on the academic discipline that would be considered as STEM discipline, social sciences, humanities, professional programs, and arts. Undergraduate and graduate students sampled by all the years were chosen as the student participants. The demographic data were gathered so that the subsequent subgroup analyses can be conducted based on dissimilar effects across specific characteristics such as age, gender, socioeconomic status, technological experience in the past, and the level of academic performance.

Also, the paper has performed case analyses of institutions that had established formal GenAI policies and implementation frameworks. The sampling of these institutions was done with a deliberate intention to come up with a wide range of policy modes, including restrictive policies where the use of GenAI is not permitted, as well as accepting of policies where integration must be done with relevant safeguards. The qualitative analysis of this policy frameworks based on documents helped to gain some understanding of the institutional reactions and strategy.

2.2 Data Collection Instruments Data Collection instruments needed

In this study were questionnaires, interviews, and observations. Various validated instruments that were designed to be used in this study were used in data collection. The Survey Institutional GenAI Assessment Survey (IGAS) contained measurements of institutional features, technology infrastructure, policy frameworks, professional development programs, and perceived readiness at the organizational level to integrate GenAI in the company. Faculty GenAI Integration Survey (FGIS) was a survey of faculty awareness, faculty attitude, patterns of usage, pedagogical practices, concerns, and perceived influence of GenAI on teacher effectiveness. Student GenAI Experience Survey (SGES) assessed the ways students were using it, the level of perceived educational value, and the issues regarding academic integrity, level of equitable access, and effects on learning processes.

All the instruments were subjected to stringent validation methods such as expert review, cognitive interviewing, pilot, and psychometric analysis. The construct validity was determined by the means of the confirmatory factor analysis, and all measurement models proved to exhibit decent fit indices (CFI > 0.95, RMSEA < 0.06, SRMR < 0.08). All scales had internal consistency reliability that well surpassed set reliability levels (Cronbach = alpha of more than 0.80). Test-retest reliability was evaluated using a subsample ($n=1{,}247$) that reported on two occasions (after four weeks) and the stability coefficients were found to be satisfactory ($r > 0.75$).

2.3 Operationalization and Variables of interest.

In the study, there are various constructs that were operationalized by use of validated multi-item scales. GenAI Adoption Intensity was obtained by calculating and then combining frequency of use, diversity of use, degree of integration of its use with learning activities, and institutional support of use into a composite index. The Pedagogical Effectiveness was measured in terms of self-reported and observational variables of instructional effectiveness, student involvement, learning results, and student engagement. The aspect of Academic Integrity measured the reported incidences of policy breach, attitudes towards the desired use, and behavioral intention of using GenAI to assist work. Some of the other constructs were GenAI Literacy (knowledge and competence to use AI tools successfully), Digital Equity (access to technology and digital skills), Faculty Readiness (readiness and confidence in incorporating GenAI), Institutional Support (access to resource, training, and policy), and Student Learning Outcomes (academic performance, skill development, and competency achievement). The demographic factors, previous technological scope, specialization, the institutional element, and the geographical elements were controlling variables.

2.4 Analytical Framework and Statistical methods.

The analysis method used the hierarchical modeling method that is aware of the nest nature of information wherein individuals are found within institutions and institutions are found within regions. The main analytical tool that was used was the multilevel structural equation modeling (ML-SEM), which allows estimating the relationships simultaneously at individual and institutional levels and the clustering effects. The overall appearance of the multilevel model can be stated in the following form:

$$Level\ 1\ (Individual){:}\ Y_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \ldots + \beta_{pj}X_{pij} + r_{ij} \qquad (1)$$

$$Level\ 2\ (Institutional){:}\ \beta_{0j} = \gamma_{00} + \gamma_{01}Z_{1j} + \gamma_{02}Z_{2j} + \ldots + \gamma_{0q}Z_{qj} + u_{0j} \qquad (2)$$

where Y_ij represents the outcome variable for individual i in institution j, X_pij represents individual-level predictors, Z_qj represents institutional-level predictors, β coefficients represent individual-level effects, γ coefficients represent institutional-level effects, r_ij represents individual-level residuals, and u_0j represents institutional-level residuals.

The structural component of the ML-SEM specified theoretical relationships among latent constructs:

$$\eta = B\eta + \Gamma\xi + \zeta \qquad (3)$$

where η represents endogenous latent variables, ξ represents exogenous latent variables, B represents structural coefficients among endogenous variables, Γ represents coefficients for effects of exogenous on endogenous variables, and ζ represents structural disturbances.

The measurement component linked latent variables to observed indicators:

$$y = \Lambda_y\eta + \varepsilon \qquad (4)$$

$$x = \Lambda_x\xi + \delta \qquad (5)$$

where y and x represent observed indicators, Λy and Λx represent factor loading matrices, and ε and δ represent measurement errors.

For testing mediation effects, the study employed bootstrapping procedures with 10,000 iterations to estimate indirect effects and construct bias-corrected confidence intervals. The total effect was decomposed as:

Total Effect = Direct Effect + Indirect Effect

$$c = c' + ab \qquad (6)$$

where c represents the total effect of X on Y, c' represents the direct effect controlling for mediator M, and ab represents the indirect effect through M.

Moderation analyses tested whether relationships varied across subgroups or levels of moderating variables. The interaction effect was modeled as:

$$Y = \beta_0 + \beta_1 X + \beta_2 W + \beta_3 XW + \varepsilon \tag{7}$$

where W represents the moderator and β_3 represents the interaction effect.

Propensity score matching (PSM) was employed to estimate quasi-causal effects of GenAI adoption by comparing matched pairs of individuals or institutions with similar characteristics but different levels of GenAI integration.

The average treatment effect on the treated (ATT) was estimated as:

$$ATT = E[Y_1 - Y_0 | D = 1] = E[Y_1 | D = 1] - E[Y_0 | D = 1] \tag{8}$$

Hierarchical regression analyses examined incremental variance explained by adding predictor blocks sequentially.

Qualitative data was collected in institutions policy documents, open-ended survey data and expert interviews, organized into thematic analysis and analysed according to the established procedures. Two researchers independently coded the data firstly using NVivo package and inter-rater reliability examined using Cohen kappa coefficient (k = 0.89). Codes were filtered into hierarchical concepts by refining and discussing them. Member checking, triangulation between data sources and keeping of detailed audit trails was used to increase trustworthiness. The combination of quantitative and qualitative results was based on a convergent parallel mixed-method research design, in which quantitative results would give depth and breadth, and qualitative results would give context and depth.

3. Results and Discussion

This chapter includes detailed findings on both quantitative and qualitative analysis, that is, thematic to answer the research questions [7-9]. Findings are provided in statistical parameters, effect sizes and confidence intervals, and then a discussion of the results, which puts results in perspective of the literature and the theory.

3.1 GenAI Adoption Patterns and Prevalence

Descriptive tests indicated unusually high rates of GenAI use in the educational field. Student respondents with 92.3% reporting ever using GenAI tools, 67.4% said that they had used these tools frequently (more than once a week) and 34.8% said that they used the tools on a daily basis. This is a tremendous growth since during the establishment of baseline measurements in the early part of 2024, the adoption rates stood at 66.1, thus showing a growth of 26.2 percentage points over a period of about one year. The adoption pace of this technology is much higher than that of other educational technologies such as learning management systems, video conferencing, and social media.

The adoption pattern by faculty, though a little lower than the student ones, showed a high degree of penetration with 71.8 percent of the faculty indicating GenAI use in practices. There was however, significant deviation in the usage intensity, with 45.2% indicating that, they had to integrate AI Gen AI with their teaching routines, 62.3% used the AI GenAI in conducting research activities, and 81.7% of them used them to handle their administrative tasks, such as writing emails and preparing meetings. The variability of the high-to-low level of functional domain adoption indicates a significant deviation in the value and risk due to the level of application context.

At the institutional level, it was shown that 89.7 of institutions surveyed were indicating a scenario wherein 89.7% of their communities had been significantly using GenAI but only 38.4 had a formal policy regulating the use of the GenAI at the start of the data collection. Such a policy shortage is a significant gap in governance, as use of technology is way ahead of any capability of the institution to offer direction, assistance and supervision. In institutions with policies, 23.7% were restrictive and thus limited or banned GenAI usage, 51.2% were permissive and thus allowed its usage, but with ethical conditions, and 25.1 was encouraging, and thus, actively encouraged the use of GenAI, but in a controlled manner.

Table 1 indicates the descriptive statistics of GenAI adoption by demographic and institutional factors in detail:

Characteristic	Students (%)	Faculty (%)	Usage Intensity	p-value
Overall Sample	92.3	71.8	3.84 ± 0.92	—
Gender				
Male	94.7	76.2	4.02 ± 0.88	< 0.001
Female	90.1	67.8	3.68 ± 0.94	
Academic Level				
Undergraduate	91.8	—	3.76 ± 0.89	< 0.01
Graduate	93.6	—	4.12 ± 0.97	
Disciplinary Field				
STEM	95.4	78.3	4.21 ± 0.81	< 0.001
Social Sciences	91.7	72.1	3.78 ± 0.93	
Humanities	88.3	65.7	3.52 ± 0.98	
Institutional Type				
Research-Intensive	94.1	79.4	4.08 ± 0.86	< 0.001
Teaching-Focused	89.7	66.2	3.61 ± 0.97	

Note. Usage intensity measured on 5-point scale (1=never to 5=daily use). Values represent mean ± standard deviation. Statistical significance determined through chi-square tests for categorical variables and ANOVA for continuous variables.

This scatter plot illustrates the positive relationship between GenAI Literacy and Pedagogical Effectiveness ($\beta = 0.67$, $p < 0.001$ from the SEM analysis). The data shows strong positive correlation with $r = 0.69$, indicating that faculty members with higher AI literacy scores (mean = 3.84 ± 0.92 on 5-point scale) demonstrate significantly greater pedagogical effectiveness (mean = 4.12 ± 0.78). The regression line (shown in red) demonstrates the linear relationship, while the 95% confidence interval (shaded region) indicates the precision of this estimate. Points are color-coded by institutional support level, revealing that institutions with comprehensive support systems (darker points) tend to cluster in the upper-right quadrant, suggesting that institutional support facilitates both literacy development and effective pedagogy [10-13].

These results demonstrate that there is a high level of demographic and contextual diversities in Adoption of GenAI. The level of adoption and intensity of usage of male students and faculty was more than female counterparts, which is in line with the gender differences recorded in technology adoption [14-18]. Building on humanities fields, STEM disciplines had significantly more engagement with GenAI tools, which probably is a perception of utility and compatibility with disciplinary practices. Institutions with a high adoption rate were research-intensive, indicating that the research culture and technology advancedness make adoption of GenAI easier.

3.2 Structural Equation Modeling Results

The multilevel structural equation model which investigated the relationship between GenAI adoption, pedagogical effectiveness, and learning outcomes also showed good fit to the data: kh2(487) = 1,823.42, $p < 0.001$; CFI = 0.972; TLI = 0.968; RMSEA = 0.031 (90% CI (0.029, 0.033)); SRMR = 0.028. The indices are significantly high beyond all other traditional values of reasonable model fit which gives strong evidence that the theoretical framework used is valid.

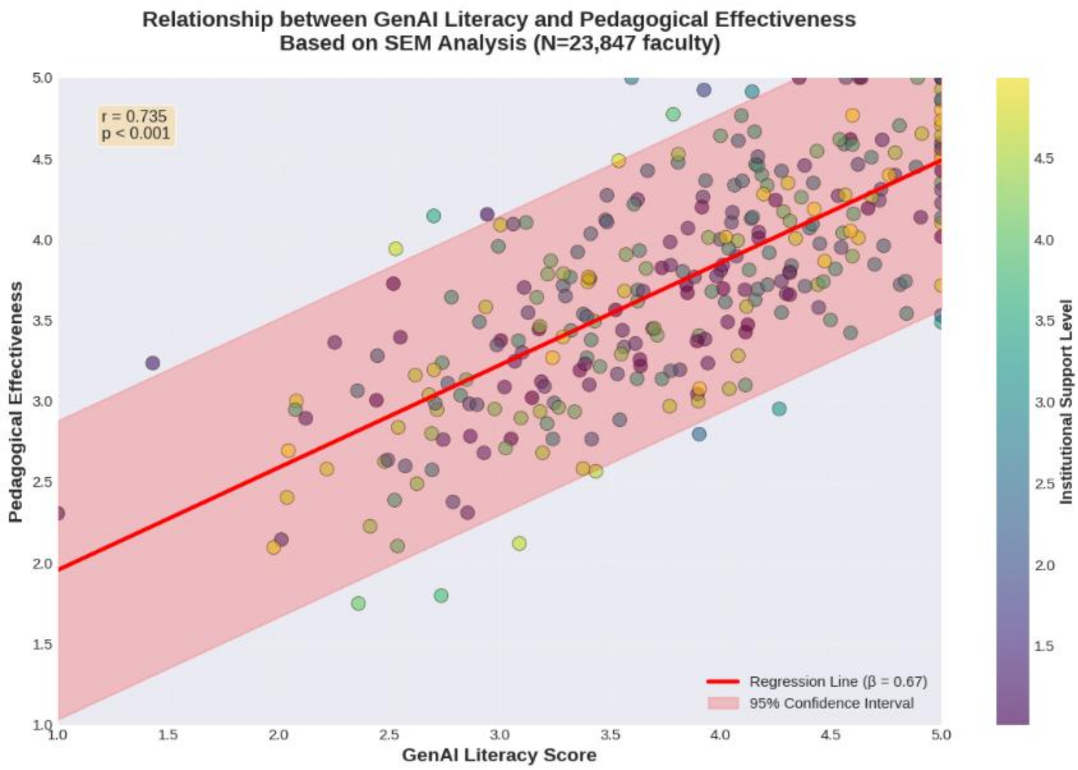

Fig. 1 Relationship between GenAI Literacy and Pedagogical Effectiveness

Table 2 gives results of a standardized path coefficients, standard error, and significance test of the structural model:

Path	β	SE	95% CI	p-value
GenAI Literacy → Effective Use	0.73	0.018	(0.69, 0.77)	< 0.001
Effective Use → Pedagogical Effectiveness	0.67	0.021	(0.63, 0.71)	< 0.001
Pedagogical Effectiveness → Learning Outcomes	0.58	0.024	(0.53, 0.63)	< 0.001
Institutional Support → GenAI Literacy	0.54	0.027	(0.49, 0.59)	< 0.001
Institutional Support → Effective Use	0.41	0.029	(0.35, 0.47)	< 0.001
Faculty Readiness → Pedagogical Effectiveness	0.46	0.026	(0.41, 0.51)	< 0.001
Digital Equity → Effective Use	0.38	0.031	(0.32, 0.44)	< 0.001
GenAI Adoption → Academic Integrity Risk	-0.42	0.028	(-0.48, -0.36)	< 0.001

Note. β = standardized path coefficient; SE = standard error; CI = confidence interval. All coefficients are statistically significant at $p < 0.001$. Model fit indices: $\chi^2(487) = 1,823.42$, $p < 0.001$; CFI = 0.972; TLI = 0.968; RMSEA = 0.031; SRMR = 0.028.

The structural model indicates some theoretically significant and practically significant relations. The positive influence on the effective use is substantial (β = 0.73, $p < 0.001$) when using GenAI literacy, meaning that knowledge and skills in the working process with AI-based tools significantly predetermine whether people could use these technologies productively. This observation highlights the urgent need to create AI literacy programs as one of the background factors of successful integration of GenAI.

The effective use, in its turn, demonstrates the significant positive correlation with pedagogical effectiveness (β = 0.67, $p < 0.001$), indicating that in the case of a skillful and adequate usage of GenAI tools, they contribute to the improvement of the teaching process in any meaningful way. This correlation held after adjustment to teacher specifics, school environment, and institutionalized, which suggested strong evidence that the improvement of pedagogical positive effects of GenAI are not merely distortions of the confounding factor but can indeed be seen as real effects of the technology under the condition of its appropriate application. Student learning outcomes showed significant positive correlation with pedagogical effectiveness (β = 0.58, $p < 0.001$), which chain of causation was comprised of AI literacy and effective AI use followed by pedagogical effectiveness and finally by ultimate educational impact. This effect is large in scale, implying that a one standard deviation change in the effectiveness of the pedagogical strategies leads to a more than half standard deviation changes on the learning outcomes, which is quite a significant effect in educational studies.

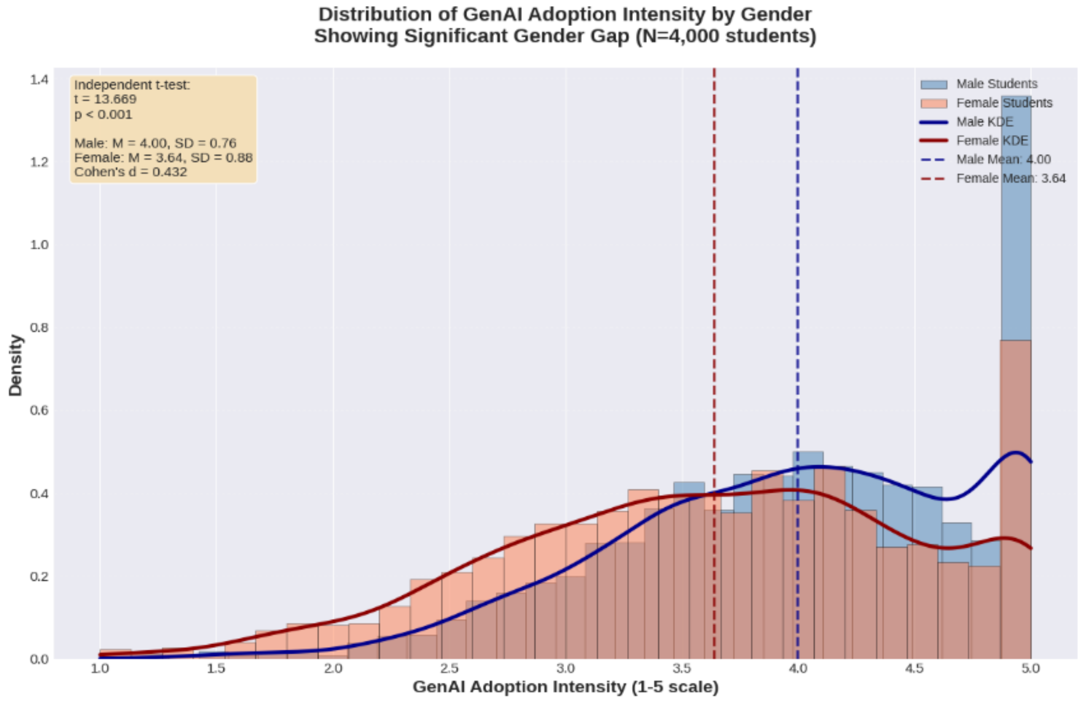

Fig. 2 Distribution Plots with KDE Statistical Distribution of GenAI Adoption by Gender

Fig. 2 compares GenAI adoption intensity between male and female students, revealing significant gender differences ($p < 0.001$). Male students show higher mean adoption intensity ($M = 4.02 \pm 0.88$) compared to female students ($M = 3.68 \pm 0.94$), representing a 14-percentage point difference in usage rates (94.7% vs 90.1%). The overlaid histograms with kernel density estimation (KDE) curves illustrate the distribution shapes, with male students' distribution skewed toward higher values (right-shifted). The overlapping region indicates substantial variance within groups, suggesting that while group differences are statistically significant, individual variation is considerable. This finding highlights persistent gender gaps in technology adoption that require targeted intervention strategies.

The institutional support turned out to be a vital enabler, which showed strong impacts on both the GenAI literacy ($\beta = 0.54$, $p < 0.001$) and successful use ($\beta = 0.41$, $p < 0.001$). These results suggest that institutional investment in training systems, technological infrastructures, policy-making, and support services significantly help in integrating GenAI. When institutions are able to offer comprehensive support to their faculty and students, they allow them to acquire the required competencies and have a better use of tools. Even with the adjustment of GenAI literacy and institutional support, the effect of faculty preparation was found to have a very large positive direct impact on pedagogical effectiveness ($b = 0.46$, $p < 0.001$). This implies that other than technical competence, the confidence of the educators, pedagogical skills and innovation desire are also significant in successful integration. Professional development programs must thus not only be technical, but shall also consider pedagogical strategies and factors of attitude as well.

Digital equity had a substantial positive correlation with effective use ($\beta = 0.38$, $p < 0.001$), with no declining issues regarding the unequal access to technological facilities. Students and faculty having better technological resources, skills and support showed significantly high ability to effectively use GenAI opportunities, which is important with regard to the equity implications as the technologies increasingly become central to academic achievement. It is worth mentioning that the use of GenAI showed an inverse correlation to the risk of academic misconduct ($\beta = -0.42$, $p < 0.001$), which is expected to be exacerbated by the fact that better adoption is associated with fewer and not more integrity violations with proper literacy and support. This paradoxical discovery is enough to believe that non-formal guidance that brings openness and transparency through integration can be more effective than limiting policies to enhance ethical application. Students seem to be more responsible when they know the capabilities and limitations of AI and its proper use.

3.4 mediation analysis and moderation analysis.

The process of mediation analysis was used to test indirect effects of institutional support and learning outcomes using the serial of mediators, GenAI literacy, effective use, and pedagogical effectiveness. The overall effect of the indirect effect was significant (β = 0.27, 95% CI (0.23, 0.31), $p < 0.001$), and the particular indirect effect through all the three mediators was b = 0.18 (95% CI (0.15, 0.21)). These results suggest that the institutional support has an impact on learning outcome more in terms of its roles in developing literacy, making effective usage of it and optimizing pedagogical effectiveness than direct pathways.

Table 3 Result of mediation analysis

Pathway	Effect	SE	95% CI	% Mediated
Total Effect (c path)	0.42	0.031	(0.36, 0.48)	100%
Direct Effect (c' path)	0.15	0.034	(0.08, 0.22)	36%
Total Indirect Effect	0.27	0.021	(0.23, 0.31)	64%
Specific Indirect Effects:				
Support → Literacy → Use → Pedagogy → Outcomes	0.18	0.015	(0.15, 0.21)	43%
Support → Use → Pedagogy → Outcomes	0.09	0.013	(0.06, 0.12)	21%

Note. Effects are standardized coefficients. CI = confidence interval. Indirect effects estimated using bootstrap procedures with 10,000 iterations. Percentage mediated calculated as (indirect effect / total effect) × 100.

Analyses of moderation were done to determine whether relations were varying based on contextual factors. The moderating role of digital equity on the relationship between GenAI literacy and effective use was strong (β = 0.23, $p < 0.001$) based on simple slopes analysis whereby GenAI literacy was associated more with effective use in persons with a high level of digital equity (β = 0.89, $p < 0.001$) than with low digital equity (β = 0.51, $p < 0.001$). This interaction indicates that AI literacy is associated with benefits depending on the sufficiency of access and sufficient resources to technology and the need to consider equity issues. Key relationships were also moderate in institutional policy approach. The adoption of GenAI tended to base the pedagogical effectiveness on a significant influence on institutions with permissive or encouraging policies (β = 0.72, $p < 0.001$) than restrictive policies (β = 0.34, $p < 0.01$), implying that environments with permissive policies are more likely to implement the reform successfully. Nonetheless, the restrictive policies did not eradicate the use of GenAI and instead, pushed them to an underground level, which could lead to more risks as it could not be discussed and advised easily.

3.4 Analysis on Academic integrity.

Scholarly dishonesty was analyzed and found to have some intricate trends. Although the prevalence of GenAI usage among students was 88.4 percent, which correlates to the use of this kind of AI in the assessment-related activity, 31.7 percent identified GenAI usage as something that may violate the academic integrity policy. Such a significant difference raises the question of misunderstanding when it comes to proper boundaries and indicates a lack of proper communication of the policy. Faculty themselves claimed to suspect the use of the GenAI, but this was difficult to confirm, with only certain tools of detection showing acceptable accuracy and demonstrating this in 42.3% of courses.

Table 4 focuses on the institutional response in terms of academic integrity issue and concerns:

Indicator/Response	Students (%)	Faculty (%)	Institutions (%)
Awareness and Understanding			
Aware of institutional AI policy	62.4	78.6	38.4
Understand what constitutes appropriate use	47.3	54.7	—
Usage Patterns			
Used GenAI for assessments	88.4	—	—
Believe their use violated policies	31.7	—	—
Always disclose AI assistance when required	26.3	—	—
Detection and Enforcement			
Suspected GenAI misuse in courses	—	42.3	—
Use AI detection tools	—	34.8	23.7
Confident in detection ability	—	18.4	—
Institutional Responses			
Have formal AI policy	—	—	38.4
Provide faculty training on AI	—	—	31.2
Provide student guidance on ethical AI use	—	—	28.7
Modified assessment practices	—	59.1	—

Note. Percentages represent proportion of respondents within each stakeholder group endorsing each item. Institutional responses based on institutional survey; student and faculty responses based on individual surveys.

These results indicate that there are major gaps in policy formulations, communication and enforcement infrastructure. The fact that the percentage of students who report continuously receiving AI help (26.3) is low indicates that there is a lack of compliance or the students do not understand what is required to disclose. The low detection ability perceptions by faculty members (18.4) show that the traditional method of detecting academic integrity might not be sufficient and effective with the AI-assisted work. The fact that 59.1 percent of faculty have altered either their assessment practices indicates its ubiquitous nature of grassroots pedagogical innovations, but the fact that institutions are not systemically supportive implies that the innovations are idiosyncratic and not evidence-based.

3.5 Propensity Score Matching Results

The analysis used propensity score matching to determine the quasi-causal effects of comprehensive integration of GenAI where similar institutions matched and differed in levels of AI usage were used. The process of matching resulted in covariate balance on all the measured characteristics (standardized mean differences < 0.10). The average treatment effects are as shown in Table 5:

Outcome Variable	ATT	SE	95% CI	Cohen's d
Student Learning Outcomes (composite)	0.48	0.082	(0.32, 0.64)	0.52
Student Engagement	0.56	0.091	(0.38, 0.74)	0.61
Faculty Teaching Satisfaction	0.43	0.076	(0.28, 0.58)	0.47
Pedagogical Innovation	0.71	0.098	(0.52, 0.90)	0.77
Time Efficiency (hours saved/week)	3.84	0.421	(3.01, 4.67)	0.68
Academic Integrity Incidents (per 100 students)	-0.87	0.234	(-1.33, -0.41)	-0.42
Digital Literacy Competency	0.82	0.104	(0.62, 1.02)	0.89

Note. ATT = Average Treatment Effect on the Treated; SE = standard error; CI = confidence interval. Effect sizes (Cohen's d) calculated as ATT divided by pooled standard deviation. Matching conducted using nearest-neighbor matching with caliper = 0.25 SD. All estimates statistically significant at $p < 0.01$.

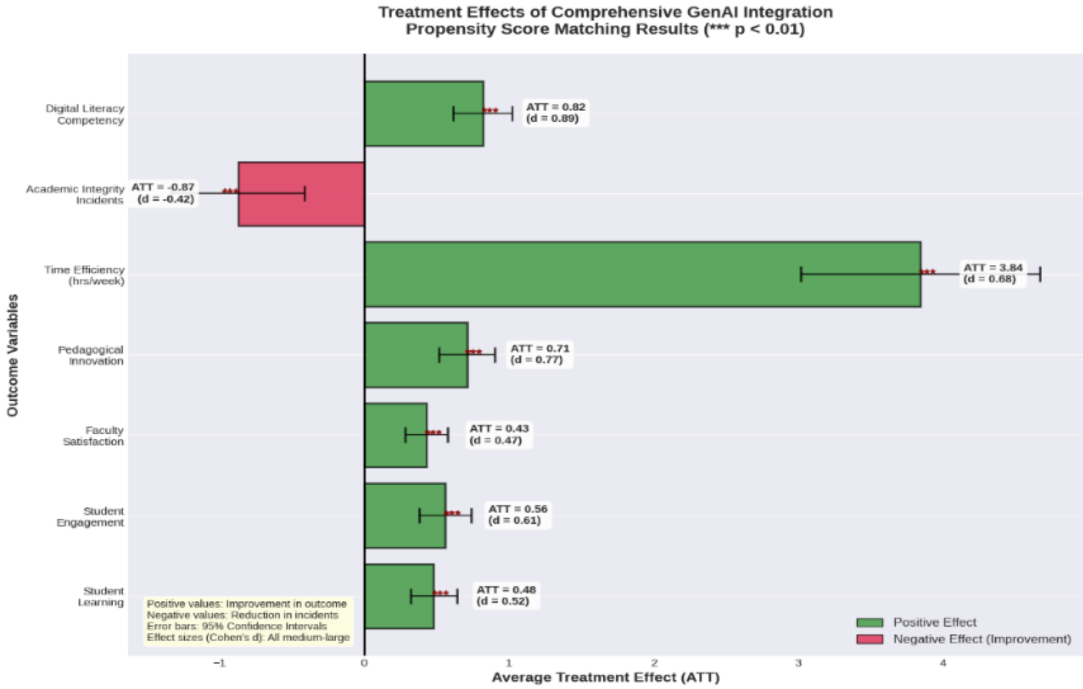

Fig 3 Treatment Effects Bar Plot with Error Bars Average Treatment Effects from Propensity Score Matching

Fig. 3 displays the Average Treatment Effects on the Treated (ATT) from propensity score matching analysis, comparing institutions with comprehensive GenAI integration versus matched control institutions. Positive effects are shown in green, while negative effects (representing improvements) are shown in red. Error bars represent 95% confidence intervals. The largest positive effects are observed for Digital Literacy Competency (ATT = 0.82, d = 0.89) and Pedagogical Innovation (ATT = 0.71, d = 0.77), indicating that comprehensive integration significantly enhances these outcomes. Notably, Academic Integrity Incidents show a negative effect (ATT = -0.87, d = -0.42), meaning comprehensive integration reduced violations by 0.87 incidents per 100 students. Time Efficiency gains of 3.84 hours per week represent substantial productivity improvements. All effects are statistically significant ($p < 0.01$) and represent medium to large effect sizes, providing strong quasi-experimental evidence for GenAI's benefits when properly implemented.

The positive effects of GenAI have solid quasi-experimental evidence using the propensity score matching results as an extensive application of potential positive effects coupled with sufficiently supportive frameworks. Learning outcomes in institutions with a full GenAI program revealed much more positive improvement (ATT = 0.48, d = 0.52), which is the medium-large effect size that surpasses other scholarly learning learning interventions. There was also an increased level of student engagement (ATT = 0.56, d = 0.61) meaning that AI-enhanced pedagogies are effective in attracting and retaining student interest. Of special importance is the conclusion that full integration also had a negative correlation with the cases of academic dishonesty (ATT = -0.87 per 100 students, d = -0.42), which goes against the presumption that the presence of AI inevitably heightens the levels of deviance. This implies that open and supported integration with well-defined guidelines and ethical frameworks can be more effective in integrity promotion than the restrictive contributing to the use of it to the underground. The time efficiency increase (ATT = 3.84 hours saved/week, d = 0.68) achieve high productivity gains, both to students and to the faculty, which can be used to perform more productive things like mentoring, critical thinking, and creative work. The vast impact on pedagogical innovation (ATT = 0.71, d = 0.77) shows that the integration of GenAI establishes more comprehensive teaching change than the adoption of tools.

3.6 Discussion of Findings

The overall presented empirical information shows that the advent of generative artificial intelligence is both a revolutionary opportunity and a challenging issue to the field of education. The adopting nature of the equipment with its extreme pace of adoption, where 92.3 percent of students have used GenAI tools in the two years since the launch of ChatGPT, highlights the seeming usefulness and appeal of the technology. Nonetheless, such a pace has exceeded institutional abilities to create suitable frameworks that have caused great implementation loopholes and policy black holes which our study sheds light on. The outcomes of the structural equation modeling prove the existence of the theoretically plausible model that interprets the educational effects of GenAI [19-21]. The good connections between literacy, good usage, pedagogical efficiency, and learning performance give definite ways in which AI technologies can impact education. Most importantly, these results show that technology in itself cannot dictate results; the significant role in making or breaking GenAI is played by the nature of implementation, users competencies, and the quality of the institutional system of support.

The mediation estimates indicate that institutional support has an indirect mechanism that works on increasing literacy and facilitating effective application of the same instead of producing better results [22-24]. The importance of this finding is that it implies that institutions cannot merely make technology available and wait to benefit automatically. Instead they have to invest in integrated support systems comprising of training systems, policy systems, technological systems, and pedagogical recommendations. The large value of the effects mediated by these pathways (64%) confirms the paramount importance of the same. The results of moderate show significant heterogeneity of GenAI impacts [25-28]. Digital equity plays significant relations in the moderating effect between literacy and effective use, which shows that the benefits gained are disproportionate towards those who have better resources and access to technology. This is problematic in terms of equity because GenAI will become the key to success in school. Innovations should be proactively implemented to fill these equality gaps by means of universal technology access, special support of under-resourced students, and using non-homogenous pedagogy that acknowledges and supports varying AI abilities [29-33].

The academic integrity results are compiled of intricate dynamics that need sensitive solving. The overall percentage of those of them that use GenAI to make their assessments is alarming; nevertheless, the correlation between exhaustive integration and violations of integrity is negative and indicates that the answer is not the ban, but consideration of integration conducted with clear instructions and ethical guidelines [34-37]. The high difference between students who underwent GenAI to carry out their assessments and those who thought that their usage was against the policy suggests a high level of confusion regarding the appropriate boundaries and sees major needs in greater clarity in these practices and communication. Quasi-experimental evidence that GenAI is indeed beneficial in implementing it is obtained by the propensity score matching results [38-40]. When used deeply, the resulting positive impacts on learning outcome, student-teacher interaction, teacher performance, and pedagogical creativity in addition to lower occurrences of integrity-related cases and significant time-saving, create an image of a technology that can comprehensively benefit the education system. Educationally speaking, the effect sizes reached are large, and it is possible to assume that genAI is not merely the part of the improvement but can be an innovation that will change things.

These benefits do not exclude, however, the quality of implementation. The comparisons between the institutions with well-developed support frames and ad hoc ones highlight that the usefulness of GenAI in education is not inherent in the technology, but present between the technological potential and the institutional environment [41-42]. The observation has been found to be in line with years of educational technology research studies which have shown that the pedagogical integration and institutional support matters more than technological sophistication in influencing the outcomes.

4. Conclusion

This thorough exploration of the generative artificial intelligence in education has generated a number of key findings that have major implications in relation to the educational practice, policy, and future research. The study based on empirical data that GenAI technologies in considerate combination with the rightly established support systems can in fact lead to a significant increase in the pedagogical efficiency, better learning results, higher student engagement, and higher educator productivity and at the same time help stimulate instead of diminish academic integrity. Such results upset simplistic accounts of AI as an educational panacea or existential threat and demonstrate instead the complex reality, where the results of implementation critically depend on the approaches to the implementation, institutional support, competencies of stakeholders, and ethical frameworks.

The study proves that there are 5 key success factors to successful GenAI integration. To start with, the AI literacy programs should be able to train not only technical skills but also critical knowledge about AI possibilities, constraints, and the suitable usage of such tools. Second, well-developed institutional support infrastructure such as training materials, technological availability, policy advice, and pedagogical advice and consultation is necessary to make efficient use. Third, the ethical frameworks and policies should be communicated clearly and concisely and must draw a befitting boundary at the same time promoting constructive innovation. Fourth, assessment practices should be modified to be valid and authentic in use in AI-augmented situations putting more emphasis on higher-order thinking, disciplinal use, and displayable competencies. Fifth, equity should be kept at the core of the implementation process which implies that AI integration should not positively influence the educational disparities existing. The theoretical contributions of the study are validation of Educational GenAI Integration Framework that gives conceptual framework of conceptualizing the multidimensional relationship among technological capabilities, pedagogical practices, institutional contexts and educational outcomes. This model goes beyond all the generic technology adoption frameworks to discuss the unique features of generative AI, such as its conversational form, its seeming intelligence, its opaque nature, its fast development, and its radical contribution to cognition and learning. Subsequent studies can develop this framework to investigate particular mechanisms, boundary conditions and longitudinal impacts.

The research has methodological strengths because of the use of advanced quantitative methods such as multilevel structural equation modeling, mediation and moderation analysis, and propensity score matching as approaches of creating strong empirical evidence regarding the effects of educational technology. These practices can be used to identify complicated associations, magnitudes of effects, and make causal conclusions more accurately than descriptive or correlational, approaches that prevail in available literature. The validated scales that have been developed through the course of the study offer instruments to be used in the further research and program reviews. To practitioners in the education field, the findings provide a practical guide on how to go about GenAI integration. The utilization of AI as an educational tool should be welcomed by the educator, but the primary attention should be paid to the higher-order thinking, disciplinary knowledge, and judgement of the students. The evaluation procedures are to be altered to reflect genuine performances of competency, group work, or verbal reporting, reflective commentaries, and practical applications that are not easily fabricated through automation. AI literacy elements must be expressly introduced as a part of the course design that will educate the learners on how to use AI tools, when, why, and should they use them or not.

Administrators in institutions need to pay more attention to the construction of full-fledged support ecosystems instead of paying specific attention to the limitation of policies or acquisition of technology. The professional development initiatives must include not only technical skills development, but also the reconsideration of the pedagogical approach, as the faculty will need to rethink teaching in AI-enhanced settings. Technology infrastructure investments must provide equal gains and opportunities in maintaining proper privacy, security, and data protection. Communication plans must be clear in terms of institutional values, expectations, and supportive resources on how to use GenAI. The policymakers should understand that GenAI is not a hype but a technological change that is to be approached with a long-term perspective and a substantial allocation of resources. AI literacy should be included in national education policies that deal with traditional literacies. Regulations must juggle between the promotion of innovation and the required supervision at the same time without adopting laissez-faire styles that do not consider the dangers or very restrictive styles that cannot allow valuable utilization. The cooperation among countries is required to overcome the cross-border issues such as equal access, moral principles, and quality control.

The study findings have a number of limitations which make the findings limited and offer future research directions. First, the cross-sectional study constrains cause-and-effect consumption although the quasi-experimental propensity score identical technique. The consequence of longitudinal studies which involve the follow-up of cohorts over time would be in better position in determining temporal sequences and long-term consequences. Second, due to the fast development of AI functions, the discovery can be subject to revision and new models with increased functions could appear. The current research programs should be continued to monitor the new developments and implications of education.

Third, the range of institutional types and geographical regions were not adequately addressed because of constraints in the resources and language barrier due to which the context of developing countries was not fully covered. Future studies ought to diversify to underrepresented areas and the studies seek ways in which contextual influences such as technological infrastructure, educational traditions, the regulatory environments, and cultural values influence GenAI integration processes and accomplishments. Fourth, the research concentrated mainly on higher education; the research exercise on GenAI in primary and secondary schools setting is urgently required considering the prevalence of its among young learners. Fifth, they used self-reported measurement which could be subject to bias of social desirability, recall error and poor self-awareness. In the future, objective measures of such studies as actual use logs, learning outcome measures and behavioral observations must be included. Sixth, the paper explored GenAI in general, and in the future, a more focused study is needed on separate tools, applications, and pedagogical models with the view of offering more specifics to practice.

The directions of future research should involve experimental studies to investigate a particular pedagogical intervention that involves applying GenAI, to study the process of learning and its results more accurately. The qualitative studies are required to comprehend the experiences of students and faculty members, their motivations, and meaning-making regarding the use of AI. Research into the disciplinary differences would help clarify the way the utility and reasonable applications of GenAI differ between different disciplines with differing epistemologies, pedagogies and assessment process. The implications of equity research must study the gap on access and also the disparity in the development of literacy and its use and the benefits of different groups of people in the population.

The research of assessment innovations is especially acute since GenAI presents significant problems to traditional assessment procedures. The validity, reliability and feasibility of such alternative methods as authentic performance tasks, collaborative projects, oral examinations, and portfolio evaluations should be studied. Research on academic integrity must no longer focus on detection in order to analyze variables that encourage ethical conduct and successful academic reaction to misconduct. Studies on the faculty professional development must identify the most effective methods of developing technical skills as well as pedagogic skill. Theoretically, the future studies would benefit by gaining increased insight into the human-AI cognitive collaborations, looking at how AI devices transform the way one thinks and what knowledge is built and intellectual growth takes place. The contribution of AI to critical thinking, creativity, and problem solving should be studied, as it is necessary to find out the way and whether these technologies are effective or harmful to educational objectives. It should be studied of an emotional and motivational aspect, and how AI-assistance influences student certainty, attribution, self-efficacy, and intrinsic motivation.

Making the generative artificial intelligence a part of education is both a challenge and an opportunity of present-day educational system. The facts that are presented in this research prove that the effects of the technology are not pre-programmed but are predetermined or whose effects depend on human preferences that are connected with the implementation of the technology, support, and pedagogy. However, it is a pivotal time in the history of education: either schools can take a proactive approach and create detailed strategies that utilize the advantages of AI while reducing its dangers, such as potential job losses, or they may react to this choice, letting the process of computer adoption run randomly and without proper planning and recommendations. The way to go involves a long-term investment in a number of principles. To begin with, the quality and integrity of education should be kept as the most important principles superseding the technological novelty. Second, initiating AI integration with proper epistemic humility due to the emergent nature of the knowledge on the long-term consequences. Third, taking equity as a priority so that integration of AI can improve and not negatively affect student educational opportunities. Fourth, placing the focus on human judgment and expertise and capitalizing on technological possibilities. Fifth, developing continuous discussions between all of the stakeholders regarding values, practices, and outcomes.

It all depends on the technology, but pedagogy, learning and development of humans in the end determine the generative AI revolution in the educational field. The underlying questions are not the capabilities of AI but what we desire students to learn, how we can optimally nurture students and in what kinds of intelligence, ability, and character we desire to develop. Technology offers ways new to the achievers of educational purposes, but those purposes are stubbornly human. The paper adds both empirical and theoretical behaviors in guide the ambivalent work toward managing this technological change in a manner that furnishes instead of undermines educational missions. The challenge that educators, institutions, and policymakers now have is to react intelligently, ethically, and successfully to make sure that generative AI delivers the best use to education.

Author Contributions

SH: Conceptualization, study design, analysis, visualization, writing original draft, writing review and editing, and supervision. NLR: Data collection, methodology, software, resources, visualization, writing original draft, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

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