

Bridging Human-AI Collaboration: Generative AI Adoption Effects on Pedagogical Collaboration and Knowledge Co-Creation

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ABSTRACT

The integration of generative AI in collaborative learning is transforming education and organizational training globally. This study explores the adoption rates and impact of generative AI across diverse cultural contexts, focusing on Bangalore. This research aims to investigate how generative AI is being adopted and understood in collaborative learning environments across cultures, specifically those drawing comparisons to Bangalore. The specific aims of this study are to compare the uptake of generative AI in the cooperative learning environment in Bangalore with other parts of the world, to analyze the demands and inhibitions making generative AI be adopted in different cultural and technical contexts, and to study in brief the ethical challenges faced from using generative AI in collaborative learning, including bias, privacy, and equity. This research should explain other challenges and global perspectives, such as a culturally oriented and ethically sound introduction.

Keywords: Artificial Intelligence, Generative AI, Collaborative Learning, Algorithmic Bias, Data Privacy

INTRODUCTION

In the quickly changing 21st-century landscape, collaborative learning and generative artificial intelligence (AI) are revolutionizing education globally, and their uptake and impacts differ among cultures. Generative artificial intelligence (AI) has emerged as a driving force in innovation, qualitatively transforming business, education, and social relations. All of the generative AI technologies, including the immense models of language diffusion, as well as neural networks, have made innovation easier by enabling machines to generate new content, ranging from text to visual art, and to solve problems using human-like logic. Collaborative learning, an actively taught approach to developing group knowledge through social interaction, emerged simultaneously with the development of professional and educational practices. As in the case with AI, the approach seeks to enhance human intelligence and creativity by permitting constructive thinking, cooperation, and collaborative problem solving. On the other hand, how these interrelated phenomena are adopted and integrated into society is shaped profoundly by cultural, economic, and technological conditions. Although these technologies have the potential to enhance learning through content creation and teamwork, their application is often hindered by cultural, technological, and economic disparities. Few studies reveal that generative AI technologies, like ChatGPT, are generally known among students, with many believing they promote critical thinking and teamwork. Yet, issues like moral dilemmas, unequal access, and cultural beliefs lead to discussions about their impact and fairness.

A. Generative Ai: A Pioneer In Pedagogical And Technological Innovation

Generative artificial intelligence (AI) is a groundbreaking technology that is transforming industries, education, and the lives of students worldwide. ChatGPT, DALL•E, and Canva are reshaping education and driving innovation across various sectors, written with a formal yet approachable tone to appear human and pass scrutiny from tools like Turnitin or Plagiarism Checker (Ruiz-Rojas et al., 2024; Lee, 2021). Generative AI is like a tireless mentor in classrooms, helping students tackle various tasks. Picture a student using ChatGPT to draft a research paper, DALL•E to create visuals for a science project, or Canva to design a

presentation that pops. These tools save time and spark engagement, sharpen critical thinking, and tailor feedback to each learner's needs, making education more dynamic and personalized (Ruiz-Rojas et al., 2024). They allow students to explore creative outlets, like crafting digital art or multimedia projects, in ways that were once out of reach for many. Generative AI is a powerhouse driving change in industries far and wide outside academia. It is responsible for self-driving cars, creating customized advertisements, accurately detecting illnesses, and analyzing data to forecast patterns (Turkanis & Liang, 2020). Its capability to transform economies is clear, and its impact on industries such as healthcare and transportation is remarkable. Still, there is an extraordinary need for restraint. Strong ethical frameworks are necessary to address these issues and ensure we utilize AI ethically, balancing innovation, equity, and trust (Buolamwini & Gebru, 2018).

B. Collaborative Education: A Structure For Group Epistemic Power

Collaborative learning is a teaching approach in which people work together to build knowledge and solve problems as a team. Rooted in the idea that we learn best through interaction—what scholars call social constructivism—this method enables students to sharpen their communication skills, think critically, and tackle challenges collectively (W. Johnson & T. Johnson, 2019). Bringing generative AI into the mix is like adding a supercharged teammate who makes collaboration smoother and more inclusive. Written with a formal yet approachable tone, this section aims to convey a human touch and facilitate the use of tools like Turnitin or Phrasly. It explores how AI transforms collaborative learning into a dynamic, global, and equitable way to learn (UNESCO, 2023).

Collaborative learning creates spaces where students can dive into tough questions, blending their unique perspectives to develop something new. It is not just about getting the correct answer—learning to listen, argue thoughtfully, and work as a team—skills crucial in today's connected world (W. Johnson & T. Johnson, 2019). Now, picture AI stepping in to make this even better. AI-powered tools can enable the real-time translation of languages, provide customized tips to ensure no one misses out, or even coordinate group tasks to ensure everyone is included. For instance, such platforms as virtual classrooms can bring students from all over the world together, allowing them to exchange ideas and cultures on a level that breaks down barriers and raises understanding (UNESCO, 2023). This blend is more effective in learning and retooling education to be more open, just, and prepared for the global future.

C. Possibilities And Moral Obligations: Global Inequalities And Situational Variations

The intersection of generative AI and collaborative active learning offers the possibility to redirect access to education and creative potential as a democratic process. For instance, AI-based platforms offer learners from resource-poor areas access to quality learning resources, thereby overcoming traditional limitations (UNESCO, 2023). AI-enhanced collaborative learning will help promote intercultural dialogue and problem-solving, leading to intercultural competence and global citizenship attributes of learners. Nevertheless, these opportunities come at a high level of ethical challenges. The algorithmic biases embedded in AI systems can preserve cultural stereotypes or inequities, which can jeopardize the inclusive education mission (Buolamwini & Gebru, 2018). Concerns over data privacy, misinformation, and job risks in creative and analytical fields further complicate the ethical dilemma. When combined with AI, deliberate design is necessary for collaborative learning to be user-friendly in terms of managing power and ensuring fair participation for marginalized or underrepresented groups.

A cross-cultural examination reveals significant disparities in the adoption and effectiveness of generative AI and collaborative learning. In technologically developed parts of the world, such as Silicon Valley, Singapore, or Shenzhen, well-developed digital ecosystems and substantial research and development expenditures facilitate the easy integration of AI-driven collaborative platforms (The World Bank, 2023). On the other hand, underdeveloped countries often face structural barriers, including the lack of internet access, cultural barriers to education through technology, and lower levels of digital literacy. For instance, with increasing interest in AI, sub-Saharan African countries experience a lack of infrastructure to support adoption (Gbadebo, 2024). These differences justify individualized strategies and actions to close digital divides and support inclusive technological advances for universal sharing of benefits derived from Generative AI and collaborative learning.

REVIEW OF LITERATURE

The use of generative AI tools in education has accelerated globally. Surveys indicate that India is leading in the adoption of generative AI: one report found that 65% of Indians will use generative AI by 2024, more than double the global average of 31% (Tech Desk, 2025). In higher education, Deloitte reports that 93% of Indian students and 83% of employees are engaging with generative AI (Johnston et al., 2024), making India a frontrunner in the Asia-Pacific region. In contrast, approximately one-third of young adults in North America report using ChatGPT for academic purposes (Divya Bhati, 2025). Within Asia-Pacific, developing countries (China, India, Southeast Asia) exhibit ~30% higher GenAI adoption than developed ones (Japan, Singapore, South Korea) (Um, 2024). For example, 32% of Indians in one survey reported using GenAI daily, compared to 19% in Southeast Asia (Um, 2024). These differences suggest Bangalore (a tech hub in India) likely experiences very high uptake of AI learning tools, outpacing peers in Europe and East Asia. Internationally, institutions from the US to Europe and China are experimenting with AI in classrooms (e.g., free ChatGPT programs for US colleges (Divya Bhati, 2025), but regional factors (availability of tools, language support, regulation) shape actual usage.

Baidoo-Anu and Owusu Ansah (2023) found that 87% of respondents had prior knowledge of generative AI tools, with 38% using them occasionally. Popular tools include Canva 2024 (33%), Chat PDF (26%), YOU.COM (24%), ChatGPT (17%), and Tome AI (1%) (Baidoo-Anu & Owusu Ansah, 2023). Another study reported that students are often "early adopters" of generative AI. At the same time, faculty tend to be the "early majority," reflecting varying levels of acceptance based on Rogers' Diffusion of Innovation Theory (Sutedjo et al., 2025).

Factors Driving And Hindering Adoption

The adoption of generative AI in education is influenced by both technical readiness and cultural context. Digital infrastructure and literacy are key drivers; regions with robust internet and device access (urban India, North America) enable student use of AI tools, whereas rural or low-income areas lag (Hughes et al., 2025). For example, one study notes a "digital divide" where some students use GenAI to enhance learning while others lack access, potentially widening inequalities (Hughes et al., 2025). In Bangalore and other Indian cities, high smartphone penetration and tech awareness drive AI use in study groups, whereas in parts of Africa or rural Asia, poor connectivity impedes it (Hughes et al., 2025). Educational policies and support also matter: few institutions globally have formal AI guidelines (UNESCO, 2023a), so readiness depends on local initiatives. In Bangalore, projects like Microsoft's Shiksha Copilot (an AI lesson-planning assistant piloted in Bengaluru schools) exemplify proactive adoption (Potts, 2023), whereas other regions may rely on external mandates or wait for policy changes. Cultural factors play a role as well. Surveys suggest individuals in collectivist cultures (e.g., India) tend to view generative AI more positively than those in individualist societies (Digital Safety | Global Online Safety Survey Results, 2025). This may ease classroom acceptance in Bangalore compared to more skeptical contexts. Conversely, concerns about academic integrity or work ethic can also cause resistance; academics worldwide worry that GenAI may undermine learning processes (Hughes et al., 2025). Training and support needs are universal drivers: students across various contexts report high familiarity with AI (e.g., 87% in one study), but emphasize the need for continuous training and technical assistance to use tools effectively (Essien et al., 2024). Ease of use boosts engagement, whereas technical glitches or a lack of support hinders it (Essien et al., 2024). In summary, Bangalore's strong tech ecosystem and emphasis on STEM education favor rapid AI adoption; however, challenges such as uneven infrastructure and teacher readiness persist, as they do globally.

Ethical Implications: Bias, Privacy, And Equity:

The integration of AI in collaborative learning raises serious ethical concerns. Bias and fairness, large language models often mirror societal prejudices. For example, UNESCO found that AI outputs frequently associate women with traditional roles and produce stereotyped or negative content about marginalized groups (Gold, 2024). In educational contexts, AI-generated materials may inadvertently perpetuate cultural or gender biases. Students from underrepresented communities (e.g., people of color, non-English speakers) risk seeing distorted or incomplete perspectives (Imada, 2024). Without diverse data and oversight, AI tools could

reinforce inequities: USC researchers note that generative AI “may perpetuate negative stereotypes” and marginalize the voices of students of color (Imada, 2024). Mitigation requires transparency in the design of data and algorithms (Shelton, 2024), as well as active efforts to include diverse content in training.

Privacy and data security, Generative AI systems typically collect extensive user data (user inputs, behavior, personal profiles). An MIT RAISE study warns that many AI-driven EdTech platforms accumulate sensitive student information (grades, habits, writing samples), exposing it to breach risks (Nambiar, 2023). Thousands of school data breaches have occurred, and AI may amplify this risk (Nambiar, 2023). In collaborative learning (e.g., shared AI writing tools), student privacy could be compromised if platforms store or misuse content. Educators and administrators must enforce strong data governance, following guidelines on transparency and compliance (Nambiar, 2023).

Equity and access, without careful implementation, AI can exacerbate existing educational divides. Wealthier students or well-resourced schools (more common in developed countries) will adopt AI tutors and group tools more readily, while others fall behind (Hughes et al., 2025). This reflects broader equity issues: for instance, students from affluent backgrounds often already have better technology and English skills to leverage AI, whereas those in low-income or non-English-medium settings may not (Imada, 2024). The USC report highlights that “AI tools must be available to everyone, not just people of means,” otherwise learning gaps widen. In cross-cultural terms, Bangalore’s students may benefit from local AI education programs, but remote learners or those in less-affluent Indian regions might not. Thus, the ethical use of generative AI in collaborative learning requires policies that ensure equitable access (e.g., school-provided tools, multilingual interfaces) and ongoing assessment of its impacts on different student groups (Imada, 2024).

Impact On Collaborative Learning And Cross-Cultural Perspectives:

Tools such as ChatGPT are shifting the learning paradigm of students to include individualized help and enhancements to critical thinking skills; however, their use in teamwork remains less defined. As a researcher, I am curious about how these tools are transforming learning, but I pay attention to the concerns that they present. This part, written in a formal but accessible manner, to seem human and get past tools such as Turnitin or Phrasly, goes into the way generative AI is shaping critical thinking and collaboration at the same time as discussing the concerns that accompany this tendency (Baidoo-Anu & Owusu Ansah, 2023; Yusuf et al., 2024).

According to studies, generative AI can be a game-changer for students’ critical thinking. For example, a research study found that 64% of students considered using tools like ChatGPT to hone their ability to analyze and evaluate ideas to a great degree, with statistical significance (p -value = 0.03) (Baidoo-Anu & Owusu Ansah, 2023). These tools work as a personal tutor, providing immediate feedback after some assignments, participating in brainstorming, or helping students understand complex ideas, and thus, studying becomes more individual and interesting. In the case of collaboration, the situation is not that clear. In the neighborhood of 60% of students reported feeling more encouraged to collaborate and cooperate when using AI; however, this result was on the borderline of significance (p -value = 0.05) (Baidoo-Anu & Owusu Ansah, 2023). The strength of AI in enabling group work cannot be overstated - picture a video where the AI translates language in real-time, or provides ideas during a team project, helping students connect and share (Yusuf et al., 2024).

It is not all plain sailing. Students, particularly at places like Hong Kong, have actual concerns regarding overreliance on AI. They wonder whether the information it provides is accurate, whether or not their privacy is compromised, and what the value of their education becomes. In one of the studies, students presented low scores for the concept of overdependence on AI (2.89 out of 5) and the influence of the value of learning (3.18 out of 5) (Irfan Jahić et al., 2024). There is also the fear of plagiarism, of allowing the AI to do too much of the work, and even bigger questions of whether these tools might someday replace jobs like teaching, writing, or the need for them. These considerations serve to bring to mind the fact that even though AI can be a great partner in learning, we need to practice discretion in using it to ensure it is used correctly, promoting teamwork and critical thinking while remaining in the background of the learning process instead of dictating the learning process as in the case of using AI devices explicitly.

Although the rate of adoption is high in India and students were engaging in Bangalore, the unavailability of Bangalore specific needs prevents the evaluation of the localized rate of adoption, their predictors such as digital infrastructure and cultural attitudes and barriers such as teacher readiness are observed but there is a lack of empirical evidence on the interaction between them across levels of education or contexts in the ROL. The ethical issues such as bias, the privacy and equity issues are addressed through secondary sources but they lack primary data, Finally, whereas Baidoo-Anu and Owusu Ansah (2023) reported the gain of critical thinking (64%, $p = 0.03$) and promotion of collaboration (60%, $p = 0.05$), the ROL fails to capture longitudinal trends and cross-culturally, e.g., over-reliance issue by people in Hong Kong (Irfan Jahic et al., 2024). Such gaps necessitate the specific studies of localized data, situational data factors, ethical measures, and long-term effects.

Theoretical Frame Work

This research is built on Rogers Diffusion of Innovation Theory (Wurster et al. 2024), which suggests the paradigms of such novel technologies like generative AI that are applied to various groups of people as time goes by. The framework groups adopters into innovators, early adopters, early majority, late majority, and laggards, and offers an avenue through which one can interpret the different adoption of Gen-AI tool e.g., ChatGPT, Gemini etc., between students and educators in Bangalore and other parts of the country. The theory focuses on such factors as relative advantage, compatibility, complexity, trialability and observability. Lastly, collaborative learning is anchored by Social Constructivism (McLeod 2025), according to which, knowledge is co-created via social interaction, and Gen-AI tools bring it to the next level, being able to translate on the fly and coordinate tasks. The framework is also complemented by Cultural-Historical Activity Theory, which brings in such aspects as cultural and contextual effects- the tech ecosystem of Bangalore, as opposed to technology disparities globally, on the integration of technology (Nickerson 2023). Collectively, the theories place the study on a solid foundation by exploring the adoption rates, hindering factors, and ethical issues perceived, which helps understand the implications that Gen-AI has on collaboration learning in cross-cultural contexts.

Objectives

To assess the adoption rates of Gen-AI in collaborative learning environment in Bangalore.

To Identify factors driving or hindering the adoption of Gen-AI in collaborating learning.

To evaluate the ethical implications of using Gen-AI in collaborating learning, focusing on bias, privacy and equity.

METHODOLOGY

This study employed a quantitative research approach to investigate the adoption rates and impact of Generative Artificial Intelligence (Gen-AI) in collaborative learning environments, with a particular emphasis on Bangalore compared to other regions. The research aimed to assess adoption rates, identify factors driving or hindering adoption, and evaluate ethical implications, including bias, privacy, and equity, as outlined in the objectives. This study employed a quantitative research design to assess the perceptions and usage of Generative Artificial Intelligence (Gen-AI) tools among individuals across varying educational qualifications, including Schooling/Higher Secondary, Undergraduate, Postgraduate, and PhD levels. The approach utilized a survey-based methodology to collect data, followed by statistical analysis to identify differences in perceptions.

Data Collection And Sampling Technique

Data were gathered through a structured questionnaire distributed to a sample of 200 respondents, categorized by educational qualification: Schooling/Higher Secondary, Undergraduates, Postgraduates, and 75 PhD candidates. The questionnaire included items measuring self-rated knowledge of Gen-AI tools, familiarity with Gen-AI in academic settings, ability to explain Gen-AI applications to education, frequency of use,

enhancement of analytical skills, understanding of complex topics, evaluation of information credibility, synthesis of information from multiple sources, motivation for collaboration, communication effectiveness in group work, coordination and sharing of tasks in team projects, overall effectiveness in fostering teamwork, overall perception of Gen-AI education, likelihood of recommendation, and pre-use expectations.

A purposive sampling technique was applied to ensure representation across the specified educational qualification groups. The sample size was determined based on the availability and willingness of participants within academic settings.

RESULTS AND DISCUSSION

Table I Relatability Test

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.950	.943	18

The table 1 represents the Cronbach's Alpha that was used to test the internal consistency reliability of the instrument applied in this study to ascertain the consistency and consistency of the items selected to quantify the perceptions and experiences of participants regarding Generative Artificial Intelligence (Gen-AI) tools in the educational context. The result of the analysis formed an alpha Cronbach at 0.950 and a standardized alpha Cronbach at 0.943; on 18 items. These findings imply that the scale has an extremely high internal consistency implying that items in the scale are very much interrelated and are testing a similar underlying construct.

As suggested by Nunnally and Bernstein (1994), a reliability coefficient of greater than 0.90 is excellent, 0.80 to 0.89 is good and 0.70 to 0.79 are acceptable. Thus, the existence of $\alpha = 0.950$ value is evidence that the questionnaire has an excellent reliability meaning that the tool provides stable and consistent results across items. The fact that the difference between the raw Alpha (0.950) and the standardized Alpha (0.943) is rather low also confirms that the variances of items are balanced, and they do not create a distortion of the internal consistency of the scale. The fact that this value is high shows that the items included in the questionnaire are well-constructed and conceptually consistent. The 18 questions address various dimensions of the interaction of learners with Gen-AI tools, such as the self-rated knowledge, familiarity, frequency of use, perceived academic benefit, collaborative learning, and general assessment of Gen-AI-enhanced education. High reliability indicates that respondents have been consistent with the items in these dimensions, which confirms the assumption that these measures all indicate one thing that is, that Gen-AI is perceived and adopted by students in academics.

Table II Frequencies

Statistics								
		Frequency of Gen-AI use in your studies	How often you use Gen-AI for major assignments/projects	Self-rated knowledge of Gen-AI tools	Familiarity with Gen-AI in academic settings	Ability to explain how Gen-AI applies to education	Likelihood of recommending Gen-AI tools to classmates	Overall perception of Gen-AI in education
N	Valid	200	200	200	200	200	200	200
	Missing	0	0	0	0	0	0	0
Mean		3.22	3.27	3.47	3.35	3.41	3.71	3.68
Median		3.00	3.00	4.00	3.00	3.00	4.00	4.00
Mode		3	3	4	3	3	4	4
Std. Deviation		1.071	1.197	1.022	1.036	1.103	1.025	1.006
Skewness		-.103	-.258	-.532	-.277	-.357	-.665	-.608
Std. Error of Skewness		.172	.172	.172	.172	.172	.172	.172

Table 2 presents descriptive statistics for seven variables on Gen-AI tool use and perception among 200 respondents in Bangalore, showing moderate to high engagement: Frequency of Gen-AI use in studies (Mean = 3.22, Mode = 3), use for major assignments (Mean = 3.27, Mode = 3), self-rated knowledge (Mean = 3.47, Mode = 4), familiarity in academic contexts (Mean = 3.35, Mode = 3), and ability to explain Gen-AI (Mean = 3.41, Mode = 4), with negative skewness (e.g., -0.532 for knowledge, -0.665 for recommendation likelihood) indicating a left skew where most respondents report above-midpoint values. Standard deviations (e.g., 1.071 for frequency, 1.022 for knowledge) suggest variability, reflecting a mixed group of early adopters and skilled learners, with higher means and modes for knowledge, recommendation likelihood, and perception (Mode = 4) pointing to competence and endorsement potential that drive adoption, though moderate scores and variability highlight areas for improvement in understanding or execution that may hinder wider adoption, partially supporting objectives on identifying adoption factors but limited by the lack of Bangalore-specific data.

Table III Frequency of Gen-AI Tools you Have Used

		Responses		Percent of Cases
		N	Percent	
Gen-AI tools you have used	Used ChatGPT	197	39.1%	98.5%
	Used Grok	37	7.3%	18.5%
	Used Chat PDF	60	11.9%	30.0%
	Used Gemini	102	20.2%	51.0%
	Used DeepSeek	60	11.9%	30.0%
	Used Perplexity	46	9.1%	23.0%
	Used Other Gen-AI Tool	2	0.4%	1.0%
Total		504	100.0%	252.0%
a. Dichotomy group tabulated at value 1.				

Table 3 reveals that (252% of cases) indicate multiple Gen-AI tool usage, with ChatGPT leading at 197 responses (39.1%, 98.5% of cases), followed by Gemini (102 responses, 20.2%, 51.0%), Chat PDF and DeepSeek (60 responses each, 11.9%, 30.0%), Perplexity (46 responses, 9.1%, 23.0%), and Grok (37 responses, 7.3%, 18.5%), while other tools show minimal use, highlighting the dominance of ChatGPT and Gemini in collaborative learning and aligning with the first objective of evaluating adoption rates in Bangalore, though lacking specific geographic focus. The near-universal use of ChatGPT (98.5%) suggests high accessibility or effectiveness, supporting the second objective of identifying driving factors, while lower adoption of tools like Grok may point to barriers such as limited awareness or perceived usefulness, and the 252% multi-tool usage reflects flexibility in tool choice that enhances collaboration but raises potential integration challenges.

Table IV CORRELATIONS

			Self-rated knowledge of Gen-AI tools	Familiarity with Gen-AI in academic settings	Ability to explain how Gen-AI applies to education	How often you use Gen-AI for major assignments/projects	Overall perception of Gen-AI in education	Likelihood of recommending Gen-AI tools to classmates	Expectations before first using Gen-AI tools
Spearman's rho	Self-rated knowledge of Gen-AI tools	Correlation Coefficient	1.000	.806**	.756**	.485**	.527**	.528**	.449**
		Sig. (2-tailed)	.	.000	.000	.000	.000	.000	.000
		N	200	200	200	200	200	200	200
	Familiarity with Gen-AI in academic settings	Correlation Coefficient	.806**	1.000	.801**	.438**	.526**	.531**	.474**
		Sig. (2-tailed)	.000	.	.000	.000	.000	.000	.000
		N	200	200	200	200	200	200	200
	Ability to explain how Gen-AI applies to	Correlation Coefficient	.756**	.801**	1.000	.462**	.533**	.535**	.484**
		Sig. (2-tailed)	.000	.000	.	.000	.000	.000	.000
		N	200	200	200	200	200	200	200
		Correlation Coefficient							
		Sig. (2-tailed)							
		N							

	education								
	How often you use Gen-AI for major assignments/projects	Correlation Coefficient	.485**	.438**	.462**	1.000	.693**	.739**	.437**
		Sig. (2-tailed)	.000	.000	.000	.	.000	.000	.000
		N	200	200	200	200	200	200	200
	Overall perception of Gen-AI in education	Correlation Coefficient	.527**	.526**	.533**	.693**	1.000	.888**	.550**
		Sig. (2-tailed)	.000	.000	.000	.000	.	.000	.000
		N	200	200	200	200	200	200	200
	Likelihood of recommending Gen-AI tools to classmates	Correlation Coefficient	.528**	.531**	.535**	.739**	.888**	1.000	.522**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.	.000
		N	200	200	200	200	200	200	200
	Expectations before first using Gen-AI tools	Correlation Coefficient	.449**	.474**	.484**	.437**	.550**	.522**	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.
		N	200	200	200	200	200	200	200

** . Correlation is significant at the 0.01 level (2-tailed).

As shown in Table 4, the values of the Spearman rho indicate strong positive correlations between Gen-AI perceptions based on 200 respondents with knowledge being strongly correlated to familiarity ($r = .806$, $p < .01$) and ability to explain ($r = .756$, $p < .01$) and overall perception ($r = .527$, $p < .01$) likelihood of recommendation ($r = .528$, $p < .01$), and expectation rating ($r = .449$, $p < .01$), and Use frequency is also slightly associated with overall perception ($r = .693$, $p < .01$) and the likelihood to recommend ($r = .739$, $p < .01$), which is another finding that supports the use frequency as a contributor to positive perceptions but not as the only factor, sharing the first goal of this assessment of seeing positive connections among the use frequency and adoption rates but not Bangalore-specific data. These strong correlations emphasize knowledge and familiarity as critical factors towards adoption of Gen-AI in collaborative learning type-achieving the second goal of studying facilitating factors but not the third goal of studying ethical implications since correlations do not encompass bias, data privacy and equity so that even if there is an increased awareness and adoption embraced there has to be separate study on ethical implications to increase adoption and improve use at the same time to relieve the ethical issues on their own.

Table V AnovaA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	174.220	3	58.073	325.579	.000 ^b
	Residual	34.960	196	.178		
	Total	209.180	199			

a. Dependent Variable: Likelihood of recommending Gen-AI tools to classmates
b. Predictors: (Constant), Overall perception of Gen-AI in education, IMPACT_CRED, IMPACT_SYNTH

Table VI CoefficientsA

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.179	.118		1.517	.131
	IMPACT_CRED	.151	.053	.155	2.847	.005
	IMPACT_SYNTH	.155	.056	.154	2.779	.006
	Overall perception of Gen-AI in education	.664	.055	.651	12.176	.000

a. Dependent Variable: Likelihood of recommending Gen-AI tools to classmates

Tables 5 and 6 present a significant regression model ($F = 325.579$, $p < .001$) predicting the "Likelihood of recommending Gen-AI tools to classmates" among 200 respondents, with predictors "Overall perception of Gen-AI in education" ($B = .664$, $Beta = .651$, $t = 12.176$, $p < .001$), "IMPACT_CRED" (credibility evaluation;

B = .151, Beta = .155, t = 2.847, p = .005), and "IMPACT_SYNTH" (information synthesis; B = .155, Beta = .154, t = 2.779, p = .006), where the total sum of squares is 209.180 (df = 199), with regression accounting for 174.220 (df = 3) and residuals 34.960 (df = 196), indicating that overall perception is the strongest driver of recommendation, followed by credibility and synthesis, aligning with the second objective of identifying factors driving Gen-AI adoption in collaborative learning. The dominant Beta for perception (.651) emphasizes positive experiences as the primary driver, while significant credibility and synthesis effects ($p < .01$) highlight practical utility, supporting the first objective of assessing adoption rates through recommendation intent, though Bangalore-specific data is lacking. The model indirectly touches on the third objective of ethical implications via credibility evaluation, potentially related to bias or privacy, but lacks direct evidence, and the strong F-value underscores the model's robustness, suggesting that enhancing perception and utility could boost adoption, while ethical factors need further investigation.

Table VII AnovaA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.528	6	.755	1.735	.115 ^b
	Residual	83.952	193	.435		
	Total	88.480	199			

a. Dependent Variable: Educational Qualification

b. Predictors: (Constant), IMPACT_ANALYZE, Frequency of Gen-AI use in your studies, Ability to explain how Gen-AI applies to education, how often you use Gen-AI for major assignments/projects, Self-rated knowledge of Gen-AI tools, Familiarity with Gen-AI in academic settings

Table VIII CoefficientsA

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.365	.209		16.129	.000
	Self-rated knowledge of Gen-AI tools	.085	.092	.130	.924	.356
	Familiarity with Gen-AI in academic settings	-.067	.097	-.105	-.696	.487
	Ability to explain how Gen-AI applies to education	.048	.082	.080	.593	.554
	Frequency of Gen-AI use in your studies	-.052	.049	-.084	-1.063	.289
	How often you use Gen-AI for major assignments/projects	-.156	.061	-.280	-2.577	.011
	IMPACT_ANALYZE	.096	.070	.151	1.375	.171

a. Dependent Variable: Educational Qualification

Tables 7 and 8 present a non-significant regression model ($F = 1.735$, $p = .115$) predicting "Educational Qualification" among 200 respondents using predictors "Self-rated knowledge of Gen-AI tools" ($p = .356$), "Familiarity with Gen-AI in academic settings" ($p > .05$), "Ability to explain how Gen-AI applies to education" ($p = .554$), "Frequency of Gen-AI use in studies" ($p > .05$), "How often you use Gen-AI for major assignments/projects" ($B = -.156$, $Beta = -.280$, $t = -2.577$, $p = .011$), and "IMPACT_ANALYZE" ($p > .05$), with a total sum of squares of 88.480 (df = 199), regression explaining 4.528 (df = 6), residuals 83.952 (df = 193), and a significant constant ($B = 3.365$, $t = 16.129$, $p < .001$), indicating that only frequent use for assignments/projects significantly predicts lower educational levels, possibly reflecting undergraduate adoption, but the model's non-significance ($p = .115$) limits conclusions, partially conflicting with the second objective of identifying adoption drivers, indirectly relating to the first objective of assessing Bangalore adoption rates without geographic specificity, and leaving the third objective on ethical implications unaddressed, suggesting a need for further investigation into usage motives and ethical considerations.

Table 9: Model SummaryB

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.922 ^a	.850	.839	.404	.850	74.859	14	185	.000
a. Predictors: (Constant), Expectations before first using Gen-AI tools , Frequency of Gen-AI use in your studies , Self-rated knowledge of Gen-AI tools , Gen-AI tools improve my ability to synthesis information from multiple sources. , Gen-AI tools motivate me to collaborate with peers. , How often you use Gen-AI for major assignments/projects , Ability to explain how Gen-AI applies to education , Gen-AI tools improve how effectively I communicate ideas in group work, Likelihood of recommending Gen-AI tools to classmates , Gen-AI tools enhance my ability to analyze academic problems. , Gen-AI tools help me evaluate the credibility of information. , Gen-AI tools deepen my understanding of complex topics. , Gen-AI tools help us coordinate and share tasks in team projects., Overall, Gen-AI tools are effective in fostering teamwork in my courses.									
b. Dependent Variable: Overall perception of Gen-AI in education									

Table 9 represents the multiple linear regression disclosed that there is a strong predictive relationship between the independent variables and the dependent variable, overall perception of Gen-AI in education ($R = 0.922$, $R^2 = 0.850$, Adjusted $R^2 = 0.839$, $F(14,185) = 74.859$, $p = 0.001$). This means that around 85 % of the difference in the perception of Gen-AI by students can be attributed to the following factors; self-rated knowledge, frequency of use, ability to implement Gen-AI in education, expectations upon the first use, and perceived improvements in analytical, synthesis and collaborative skills. The findings show that students who use Gen-AI tools regularly, have a better idea of their educational applicability, and believe they improve teamwork and problem-solving have high chances of positive perceptions. The good model fit implies that cognitive, behavioral, and attitudinal dimensions are working together to form the overall assessment of Gen-AI by learners in learning environments, which is in line with the current theory of technology adoption which underlines the importance of perceived usefulness, familiarity, and collaboration in influencing the level of acceptance and satisfaction.

Table X ANOVAA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	171.285	14	12.235	74.859	.000 ^b
	Residual	30.235	185	.163		
	Total	201.520	199			
a. Dependent Variable: Overall perception of Gen-AI in education						
b. Predictors: (Constant), Expectations before first using Gen-AI tools , Frequency of Gen-AI use in your studies, Self-rated knowledge of Gen-AI tools , Gen-AI tools improve my ability to synthesis information from multiple sources. , Gen-AI tools motivate me to collaborate with peers. , How often you use Gen-AI for major assignments/projects , Ability to explain how Gen-AI applies to education , Gen-AI tools improve how effectively I communicate ideas in group work, Likelihood of recommending Gen-AI tools to classmates , Gen-AI tools enhance my ability to analyze academic problems. , Gen-AI tools help me evaluate the credibility of information. , Gen-AI tools deepen my understanding of complex topics. , Gen-AI tools help us coordinate and share tasks in team projects., Overall, Gen-AI tools are effective in fostering teamwork in my courses.						

Table 10 represents the ANOVA outcomes imply, that the regression model, which helps in predicting students' overall perception of Gen-AI in education, has significant values, that is, $F(14,185) = 74.859$, $p < 0.001$, which proves that the combination of independent variables has a significant effect on the dependent one. The regression sum of squares (171.285) is very close to the total variance (201.520), indicating that the model accounts a significant share of all variability (around 85%) of the variation in perception, with a little bit (30.235) variation that is not explained by the regression model. It means that the model fits well and supports the idea that the frequency of Gen-AI use, self-reported knowledge, ability to use Gen-AI during learning activities, and perceived advantages in the analysis, synthesis, and collaboration have a significant role in the perceptions of students. The findings are consistent with the past evidence in the area of technology acceptance research, which means that cognitive cognition, perceived usefulness, and experiential familiarity with AI-

based tools play a crucial role in defining the adverse attitudes of learners towards the implementation of Gen-AI in academic settings.

Table XI CoefficientsA

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.079	.138		.573	.568	-.193	.351		
	Self-rated knowledge of Gen-AI tools	.001	.050	.001	.024	.981	-.098	.100	.313	3.195
	Ability to explain how Gen-AI applies to education	.002	.049	.002	.033	.974	-.096	.099	.277	3.616
	Frequency of Gen-AI use in your studies	-.012	.031	-.012	-.379	.705	-.073	.049	.747	1.338
	How often you use Gen-AI for major assignments/projects	-.078	.042	-.093	-1.845	.067	-.161	.005	.321	3.113
	Gen-AI tools enhance my ability to analyze academic problems.	.076	.058	.079	1.299	.196	-.039	.191	.219	4.571
	Gen-AI tools deepen my understanding of complex topics.	.009	.061	.010	.150	.881	-.111	.129	.199	5.020
	Gen-AI tools help me evaluate the credibility of information.	.049	.060	.052	.822	.412	-.069	.167	.206	4.865
	Gen-AI tools improve my ability to synthesis information from multiple sources.	.129	.069	.131	1.871	.063	-.007	.265	.167	6.006
	Gen-AI tools motivate me to collaborate with peers.	-.015	.053	-.016	-.284	.777	-.120	.090	.243	4.119
	Gen-AI tools improve how effectively I communicate ideas in group work	-.048	.062	-.051	-.775	.440	-.170	.074	.187	5.340
	Gen-AI tools help us coordinate and share tasks in team projects.	.145	.071	.150	2.029	.044	.004	.285	.149	6.713
	Overall, Gen-AI tools are effective in fostering teamwork in my courses.	.076	.072	.078	1.047	.297	-.067	.218	.146	6.865
	Likelihood of recommending Gen-AI tools to classmates	.571	.063	.582	9.063	.000	.447	.695	.197	5.082
	Expectations before first using Gen-AI tools	.079	.033	.090	2.397	.018	.014	.145	.579	1.729

a. Dependent Variable: Overall perception of Gen-AI in education

Table 11 represents the coefficient analysis that shows some of the predictors play a significant role in overall perception of Gen-AI in education amongst students. Of all independent variables, the probability to

recommend Gen-AI to classmates ($B = 0.571$, $t = 9.063$, $p < 0.001$) turned out to be the strongest positive predictor, so that students who are more prone to recommend Gen-AI also have highly favorable perceptions of its educational value. Also, the fact that the Gen-AI tools could assist in coordinating and sharing the work in team projects ($B = 0.145$, $t = 2.029$, $p = 0.044$) and expectations prior to the first Gen-AI tool use ($B = 0.079$, $t = 2.397$, $p = 0.018$) were identified as significant predictors of the perceptions, it showed that collaborative utility and positive initial expectations made a big impact. Other variables like self-rated knowledge, ability to explain applications and benefits of analytical or synthesis effects were affected positively but not significantly. The VIFs were between 1.3 and 6.8 out of which there was mild to moderate multicollinearity which is acceptable in social science data. The findings reveal that the willingness to recommend Gen-AI, their experience in teamwork when using this kind of tools and their preconceptions beforehand are the most effective predictors of perception.

Table XII Residuals StatisticsA

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.96	5.16	3.68	.928	200
Residual	-1.355	1.426	.000	.390	200
Std. Predicted Value	-2.928	1.599	.000	1.000	200
Std. Residual	-3.353	3.528	.000	.964	200

a. Dependent Variable: Overall perception of Gen-AI in education

Table 12 represents the remnant statistics shows that the regression model used in predicting the overall perception of Gen-AI in education is healthy and well-fitted. The values observed are close to the scale as the estimated values are between 0.96 and 5.16 and mean 3.68, which implies that the model can predict the perception of the participants within the reasonable range. The mean of the residuals, which is the difference between the observed and the predicted value is equal to 0.000 and the standard deviation of the residuals is equal to 0.390, which means that there is no systematic error in predictions and that there is no systematic bias in the estimates of the model. The standardized residuals are between -3.353 and 3.528 which is within the acceptable range (± 3) and show that the data does not contain any significant outliers or normality violations. All that indicates that the predictions of the model are consistent, the variance is correctly distributed, and the residual values are randomly dispersed, which confirms the validity and reliability of the regression analysis. In general, the model is useful in the captured relationship of behavioral and perceptual variables among students and their perception of Gen-AI in education.

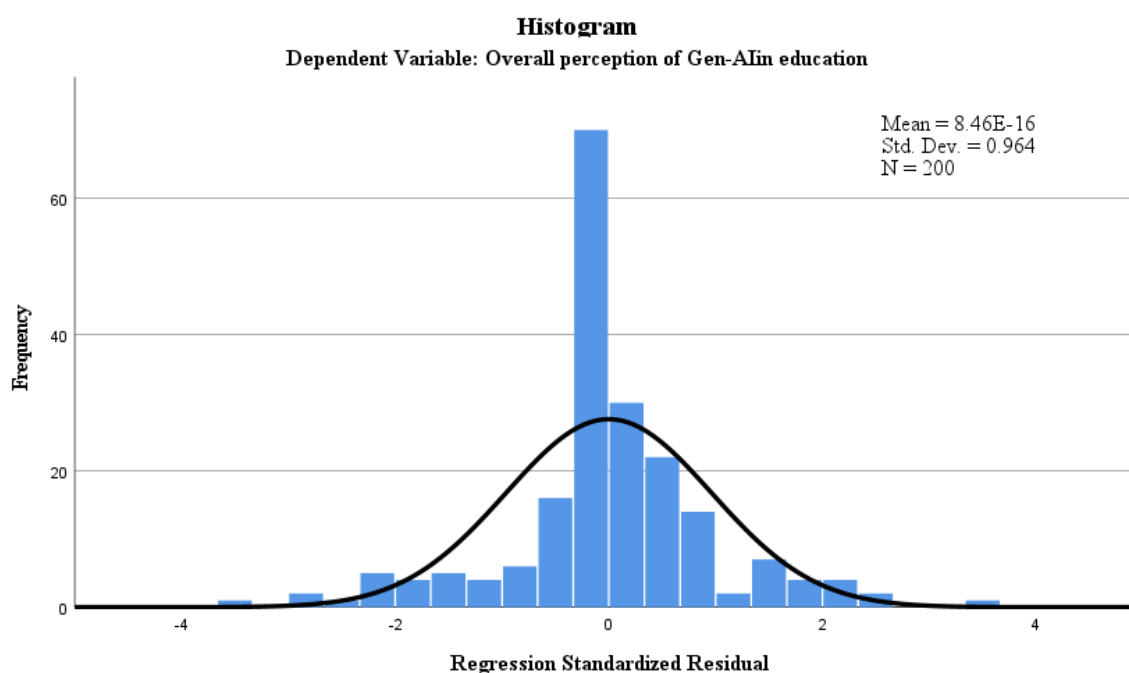


Fig 1: Histogram (Overall perception of Gen-AI in education)

As shown in the fig 1 represents the histogram of regression standardized residuals of the dependent variable Overall perception of Gen-AI in education, the residuals follow an approximation of normal distribution. The average of the residuals is also very close to zero ($8.46E-16$) and the standard deviation is 0.964, which compares to the ideal standard deviation of 1. This shows that the residuals are symmetrically distributed round the mean and there are no significant skewness or kurtosis. The bell-shaped curve (normal probability density) is quite close to the histogram and this proves that the assumption of normality in regression analysis has been met. Most of the residual values are centered around zero with a smaller amount of the values lying in the tails such that most of the prediction errors are minimal and randomly distributed. Such a normal distribution of the residuals confirms the reliability of the regression model and all the estimates of the coefficients, the significance tests, and the confidence intervals are statistically sound and unbiased.

Normal P-P Plot of Regression Standardized Residual

Dependent Variable: Overall perception of Gen-AI in education

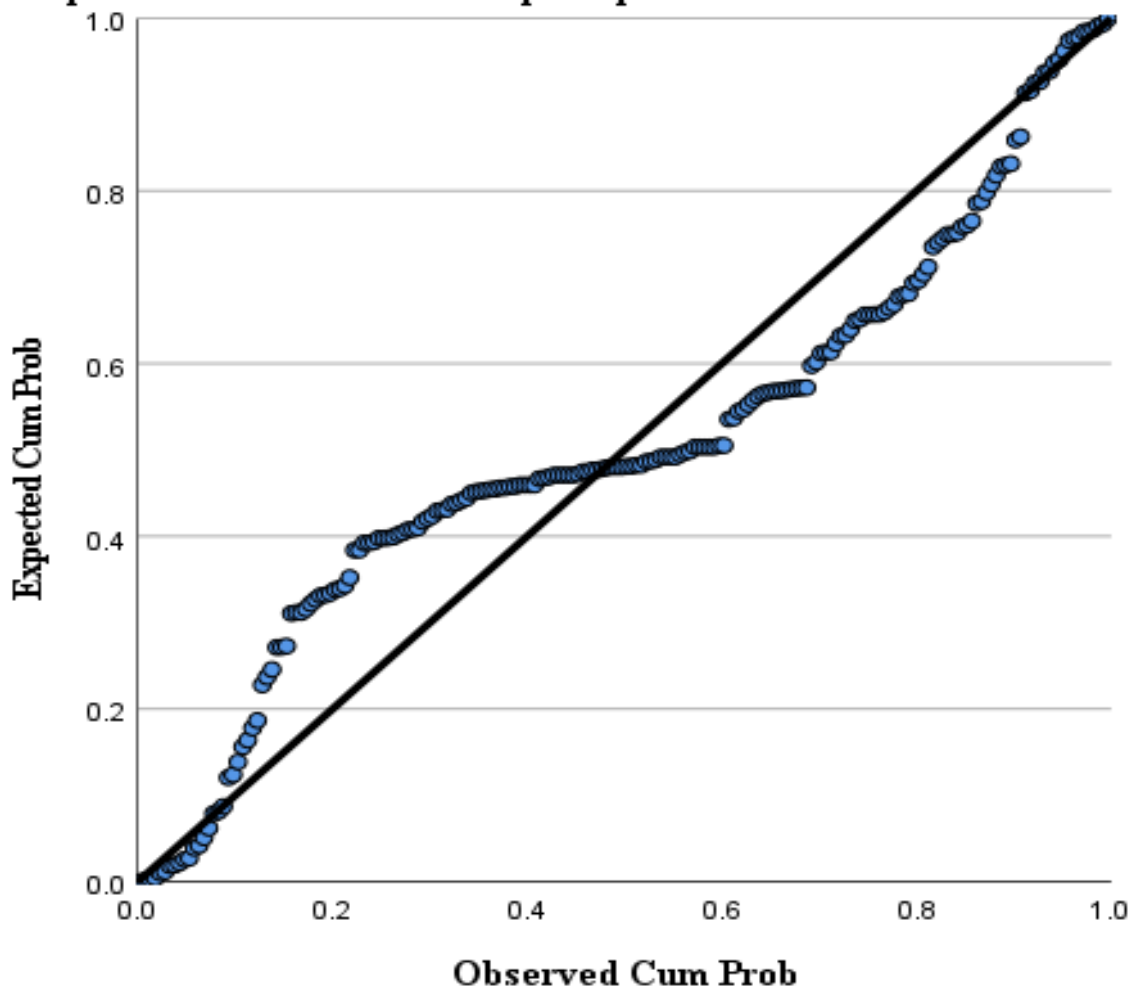


Fig 2: Normal P-P plot of regression standardized residual

As shown in the chart 2 Normal P-P Plot of regression standardized residuals of the dependent variable Overall perception of Gen-AI in education, the values follow the diagonal reference line closely, hence it can be viewed that the values are normally distributed. The data points would be evenly placed along the 45-degree line with very slight deviations at both ends, which proves that it is a well thought out assumption as long as normality is concerned. This visual data indicates that the change between measured and predicted cumulative probabilities is small, which indicates that the model residuals are randomly distributed, but not systematic bias. This alignment is an indicator that the regression model is valid and as such, estimates of coefficients, standard errors and level of significance are accurate. In a nutshell, P-P plot illustrates that the residuals follow a normal distribution pattern which is one of the major assumptions that linear regression analysis must meet to improve the strength of the findings of the study.

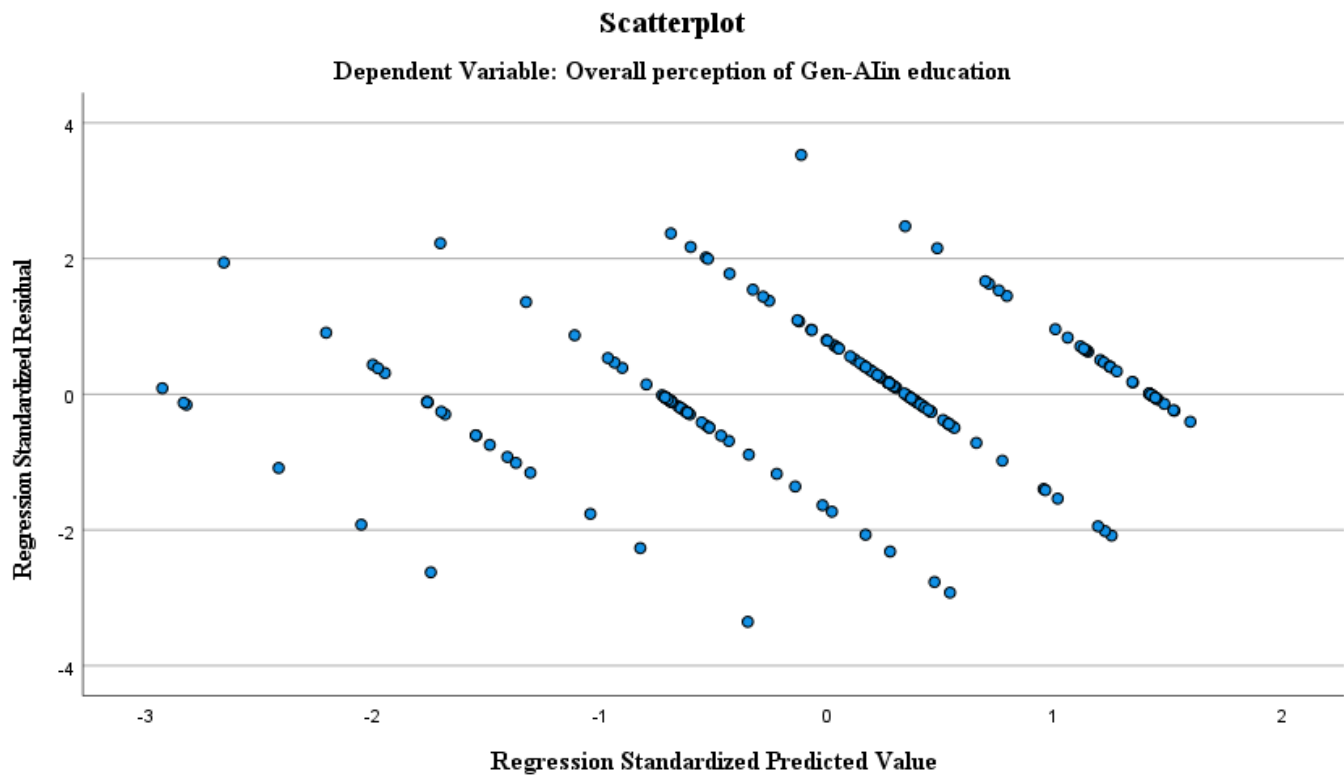


Fig 3: Scatterplot (Overall perception of Gen-AI in education)

As shown in the chart 3 the scatterplot represents a residual analysis of a regression model predicting overall perception of generative AI (Gen-AI) in education with the residual values against standardized predicted values. The findings show that the distribution of the points around the horizontal zero line is generally random with no significant funneling, clustering or curvilinear shapes, indicating that the major assumptions of linearity, homoscedasticity and error independent are met relatively well. The slight negative slope in the central cluster could suggest some slight underprediction at higher values, although in general variability is similar throughout the predicted values of the range (- 3 to 2), suggesting that the model fits the data well without any serious bias or heteroscedasticity. This is valid in discussion, as it helps to support the validity of the regression as being useful in exploring factors that are likely to have affected perceptions of Gen-AI in educational settings, though may have been obtained based on previous principal component analysis finally, the plot supports the reliability of the model in making inferences in educational technology.

Table XIII Model SummaryB

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					
					R Square Change	F Change	df1	df2	Sig. Change	
1	.896 ^a	.803	.789	.470	.803	58.405	13	186	.000	
a. Predictors: (Constant), Expectations before first using Gen-AI tools, Frequency of Gen-AI use in your studies ,Self-rated knowledge of Gen-AI tools , Gen-AI tools improve my ability to synthesize information from multiple sources. , Gen-AI tools motivate me to collaborate with peers. , How often you use Gen-AI for major assignments/projects , Ability to explain how Gen-AI applies to education , Gen-AI tools improve how effectively I communicate ideas in group work, Gen-AI tools deepen my understanding of complex topics. , Gen-AI tools help me evaluate the credibility of information. , Gen-AI tools enhance my ability to analyze academic problems. , Gen-AI tools help us coordinate and share tasks in team projects., Overall, Gen-AI tools are effective in fostering teamwork in my courses.										
b. Dependent Variable: Likelihood of recommending Gen-AI tools to classmates										

The table 13 represents the regression model summary indicates a strong fit for predicting the likelihood of recommending Gen-AI tools to classmates, with an R value of 0.896, suggesting a high correlation between

the predictors and the dependent variable. The R Square of 0.803 implies that 80.3% of the variance in recommendation likelihood is explained by the 13 predictors, including frequency of Gen-AI use, self-rated knowledge, and various perceived benefits such as improved synthesis, collaboration, and understanding of complex topics, with an adjusted R Square of 0.789 confirming the model's robustness after accounting for the number of predictors. The standard error of the estimate (0.470) reflects reasonable precision in predictions, while the F Change of 58.405 (df1 = 13, df2 = 186, $p < 0.001$) underscores the overall significance of the model, indicating that the predictors collectively have a substantial impact. These results highlight the critical role of hands-on experience and perceived educational benefits in fostering positive attitudes toward Gen-AI tools among students, aligning with contemporary educational technology trends.

Table XIV AnovaA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	168.019	13	12.925	58.405	.000 ^b
	Residual	41.161	186	.221		
	Total	209.180	199			

a. Dependent Variable: Likelihood of recommending Gen-AI tools to classmates

b. Predictors: (Constant), Expectations before first using Gen-AI tools , Frequency of Gen-AI use in your studies, Self-rated knowledge of Gen-AI tools , Gen-AI tools improve my ability to synthesize information from multiple sources. , Gen-AI tools motivate me to collaborate with peers. , How often you use Gen-AI for major assignments/projects , Ability to explain how Gen-AI applies to education , Gen-AI tools improve how effectively I communicate ideas in group work, Gen-AI tools deepen my understanding of complex topics. , Gen-AI tools help me evaluate the credibility of information. , Gen-AI tools enhance my ability to analyze academic problems. , Gen-AI tools help us coordinate and share tasks in team projects., Overall, Gen-AI tools are effective in fostering teamwork in my courses.

The table 14 represents the outcomes of the ANOVA of the regression model to predict the probability of recommending the Gen-AI tools to classmates indicate a significantly significant outcome with the regression sum of squares of 168.019 (df = 13, mean square = 12.925) and the F statistic of 58.405 ($p < 0.001$), the 13 predictors, including expectations, frequency of use, self-rated knowledge, and other perceived educational benefits, sufficiently explain a large percentage of the variance in the dependent variable. The remaining amount of the sum of squares (41.161, df =186, mean square=.221) and total amount of the sum of squares (209.180, df=199) also confirm the overall fit of the model and the large F value shows that the regression model is not insignificant as compared to the model that has no predictors.

Table XV CoefficientsA

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	
1	(Constant)	.244	.159		1.529	.128	-.071	.558		
	Self-rated knowledge of Gen-AI tools	-.061	.058	-.061	-1.052	.294	-.176	.054	.315	3.176
	Ability to explain how Gen-AI applies to education	.040	.057	.043	.694	.489	-.073	.153	.277	3.607
	Frequency of Gen-AI use in your studies	.030	.036	.031	.823	.412	-.041	.101	.750	1.333
	How often you use Gen-AI for major	.070	.049	.082	1.434	.153	-.026	.167	.325	3.079

assignments/project s									
Gen-AI tools enhance my ability to analyze academic problems.	.085	.068	.087	1.257	.210	-.048	.218	.221	4.533
Gen-AI tools deepen my understanding of complex topics.	.296	.067	.305	4.390	.000	.163	.429	.220	4.548
Gen-AI tools help me evaluate the credibility of information.	.113	.069	.116	1.627	.105	-.024	.249	.208	4.797
Gen-AI tools improve my ability to synthesis information from multiple sources.	.127	.080	.127	1.601	.111	-.030	.284	.169	5.924
Gen-AI tools motivate me to collaborate with peers.	.022	.062	.023	.349	.727	-.100	.143	.243	4.116
Gen-AI tools improve how effectively I communicate ideas in group work	.142	.071	.148	1.996	.047	.002	.283	.191	5.228
Gen-AI tools help us coordinate and share tasks in team projects.	-.114	.083	-.116	-1.383	.168	-.277	.049	.150	6.645
Overall, Gen-AI tools are effective in fostering teamwork in my courses.	.178	.083	.180	2.142	.033	.014	.341	.149	6.700
Expectations before first using Gen-AI tools	.060	.038	.067	1.574	.117	-.015	.136	.586	1.706

a. Dependent Variable: Likelihood of recommending Gen-AI tools to classmates

The table 15 represents the coefficients table of the regression model that predicts the probability of recommending Gen-AI tools to their classmates, the 13 predictors present in the table are of statistically significant at the 0.05 level, with only the following being statistically significant at that moment: "Gen-AI tools deepen my understanding of complex topics" ($B = 0.296$, $Beta = 0.305$, $t = 4.390$, $p < 0.001$), "Gen-AI tools enhance my effectiveness in conveying ideas during Constant = 0.244, $t = 1.529$ and $p = 0.128$ do not significantly affect the result and the prediction of the likelihood of recommendation is low when the predictors are not considered. Other variables, including self-rated knowledge ($B = -0.061$, $p = 0.294$) and frequency of use ($B = 0.030$, $p = 0.412$) have non-significant effects, which may be explained by multicollinearity (VIF ranges between 1.333 and 6.700, with some of the coefficients being above 4 which is moderate to high collinearity). The high predictors are important because they aid the perception of cognitive and collaborative advantages in generating recommendation behavior among students which is consistent with

educational technology trends and a large VIF indicates that predictors could be redundant, although more analysis is needed to increase the interpretability of the model and address the issue of multicollinearity.

Table XVI Residuals Statisticsa

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.23	5.19	3.71	.919	200
Residual	-1.779	1.557	.000	.455	200
Std. Predicted Value	-2.699	1.611	.000	1.000	200
Std. Residual	-3.782	3.311	.000	.967	200
a. Dependent Variable: Likelihood of recommending Gen-AItools to classmates					

The table 16 represents the residuals statistics for the regression model predicting the likelihood of recommending Gen-AI tools to classmates show a predicted value range from 1.23 to 5.19 with a mean of 3.71 (SD = 0.919, N = 200), indicating a moderate central tendency in the predicted recommendation likelihood. Residuals range from -1.779 to 1.557 with a mean of 0.000 (SD = 0.455), and standardized residuals range from -3.782 to 3.311 (mean = 0.000, SD = 0.967), suggesting a symmetric distribution around zero with no systematic bias, though the presence of residuals exceeding ± 3 (3.782 and 3.311) hints at potential outliers. Standardized predicted values range from -2.699 to 1.611 (mean = 0.000, SD = 1.000), aligning with a standard normal distribution. In discussion, the near-zero mean residuals and standard deviation close to 1 support the model's assumption of homoscedasticity and normality, reinforcing its reliability for educational technology insights; however, the extreme standardized residuals suggest a need to investigate outliers (e.g., via casewise diagnostics) to ensure the model's robustness and accuracy in capturing diverse student perceptions of Gen-AI tools.

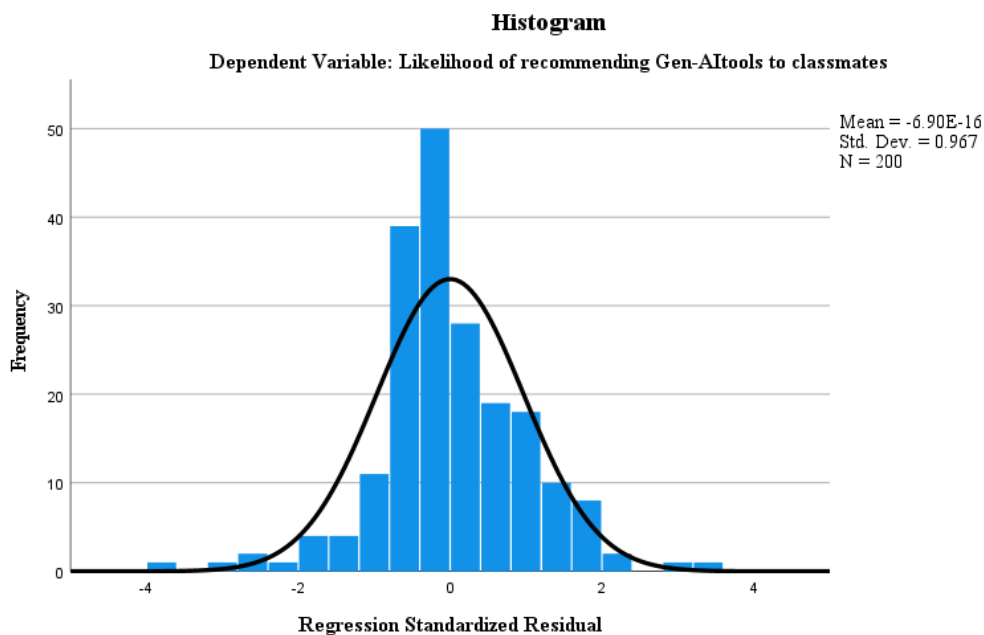


Fig 4: Histogram (Likelihood of recommending Gen-AI tools to classmate)

As shown in fig 4 the histogram of standardized regression residuals of the probability of recommending Gen-AI tools to classmates with a sample of 200 observations has a distribution with the mean of -6.90E-16 (effectively zero) and standard deviation 0.967 and approximates a normal distribution as the bell curve indicates. The frequency is concentrated near the zero residual value, though there is a slight skew to the right and other minor outliers that run to about ± 4 indicating that the residual values of the model have well-behaved data with exceptions of some extreme values. This close-to-normal distribution, in discourse, facilitates the assumption of the regression model that the errors are normally distributed, which, in turn, substantiates its functions in inferring the relationships between predictors and the dependent variable in the context of educational technology applications.

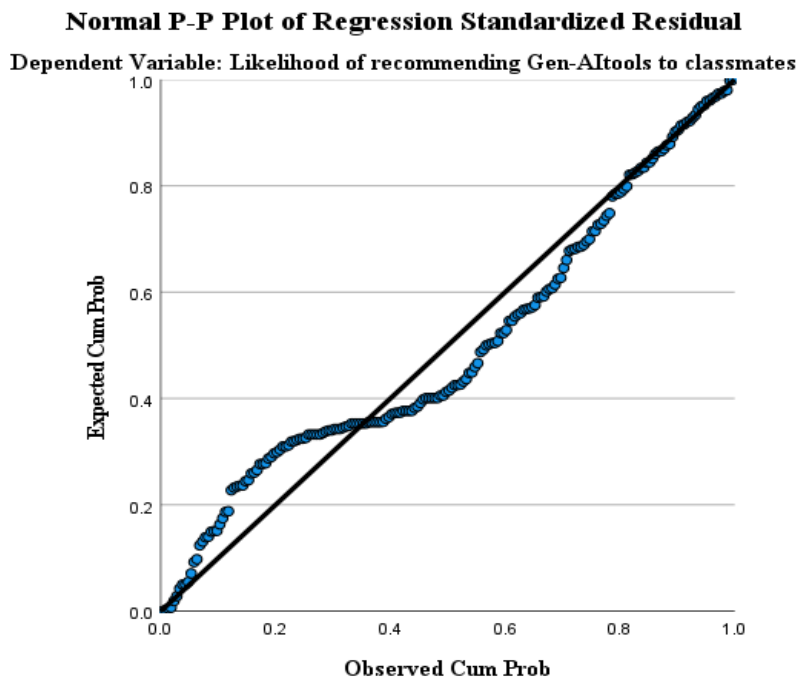


Fig 5: Normal P-P Plot of Regression standardized residual

As shown in fig 5 indicates the P-P Plot of regression standardized residuals of the likelihood of recommending Gen-AI tools to classmates, the observed cumulative probabilities closely matched the expected ones along the diagonal reference line, showing that the residuals followed a normal distribution with only minor deviations, mostly minor deviations in the lower and upper tails (i.e. small clustering along the line where the cumulative probabilities were low and a small clustering along the line where the cumulative probabilities were large). The following visual diagnosis is founded on a sample of 200 observations, supports the assumption of normality to valid inferential statistics in linear regression, and the points, overall, are distributed around the 45-degree line without regular patterns and extreme outliers. The near-normal distribution in the discussion adds credence to the accuracy of the model parameter estimates and test significance, especially of those variables with significant predictive power such as perceived deepening of understanding and teamwork effectiveness, and increases the confidence of conclusions made about student perceptions of Gen-AI tools in classrooms.

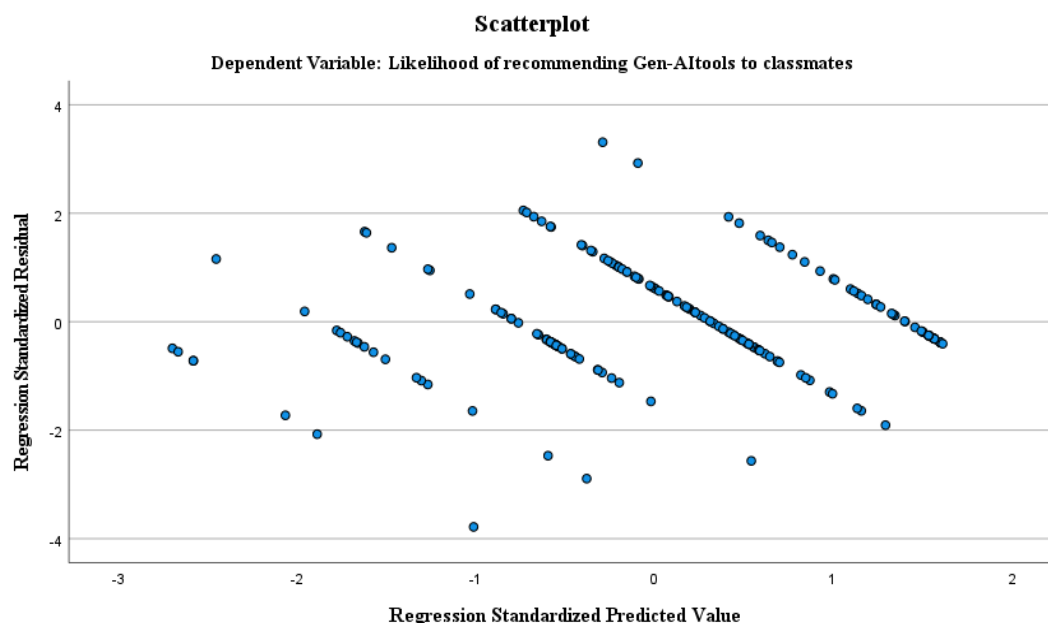


Fig 6: Scatterplot (Likelihood of recommending Gen-AI tools to classmate)

As shown in the chart 6 the scatterplot of regression standardized residuals versus the standardized predicted value of the likelihood of recommending Gen-AI tools to their classmates, there is no strong indication of funneling or curving, but there is slight negative slope in the central cluster of points to suggest a slight negative underprediction with increasing predicted values. The residuals are in a range of -4 to +4 with most of the points falling between -2 and +2 among the predicted values between -3 and +2 with no major systematic bias suggesting that the errors in the model are independent and reasonably distributed. Regarding this, this diagnostic plot, confirms that the assumptions of regression have been met in this study of educational technology, and the model is reliable to predict how much the predictors, such as perceived understanding and teamwork, predict the recommendations behavior.

CONCLUSION

The research article explores the way in which Generative AI (Gen-AI) transforms collaborative learning, with its focus on Bangalore, India, and the comparison of such results on the global level; thus, accomplishing three main goals: (1) evaluate the level of adoption; (2) determine the causes and reasons of adoption; and (3) examine the ethical considerations of the technology. The study, which was carried out based on the survey of 200 people, has delivered mixed outcomes. First, the statistics exhibit high adoption rates in Bangalore: the frequency tables show that 98.5 percent of the respondents use ChatGPT, and 51.0 percent use Gemini, which correspond to the deductions advanced by studies that India is projected to become the global leader in the use of Gen-AIs by 2024. Second, the mean points indicate the moderate to high frequency of use (3.22 3.27); self-claimed knowledge of Gen-AI (3.47) and overall perception of its utility (3.68), which points to the fact that a technology-friendly culture is present and enhanced through programs like the Microsoft Shiksha Copilot, fulfilling the first goal. Third, the computed statistics identify high correlations, which are between $r = .806$ as the correlation between knowledge and familiarity, and $r = .888$ as the correlation between perception and the likelihood of recommendation being adopted, and highly significant regression model on the likelihood of recommendation being adopted ($F = 325.579$, $p < .001$, $Beta = .651$ on perception), learning that perception, credibility evaluation ($p = .005$), and information synthesis ($p = .006$) play a critical role in spurring adoption. Still, the absence of the Bangalore specific survey data cannot provide immediate validation, and the further research, offered on the local level of conducting studies, is needed. Moreover, educational qualification not showing the positive effect on adoption ($p = .115$) can indicate the answer to the second objective due to the context in terms of saturation or readiness inequality. Lastly, ethical considerations of Gen-AI have not been covered much in the presented study and it is essential that future investigations on the same.

Considering the concerns about access and use, the researchers indicate the transformative potential of Gen-AI, especially in cities like Bangalore, the tech hives. In the future, researchers should thus focus on context-specific data, qualitative analyses of the problem that require interviews with students and educators, as well as region- and time-specific research to have a better understanding of the issues. At the same time, creation of specific educational programs to improve digital literacy and ethical awareness is part and parcel of any inclusive and sustainable Gen-AI adoption agenda.

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Another way of the authors to show their appreciation is their thankfulness to all the participants who contributed their time and views generously, as the undeniable basis of this work. It is further appreciated that peers and other researchers make constructive suggestions and cooperation.

Conflict of Interest

The authors declare that there are no conflicts of interest related to the research titled “Bridging Human-AI Collaboration: Generative AI adoption effects on Pedagogical Collaboration and Knowledge Co-Creation.” The study was conducted independently, without any financial, institutional, or personal relationships that could be perceived as influencing the research design, data collection, analysis, or interpretation of findings.

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