Sociology & Cultural Research Review (SCRR)
Available Online: https://scrrjournal.com
Print ISSN: 3007-3103 Online ISSN: 3007-3111
Platform & Workflow by: Open Journal Systems
https://doi.org/10.5281/zenodo.23766064

Adoption of Generative Artificial Intelligence Tools for Teaching and Learning at Graduate Level in Multan, Pakistan: An Extended Technology Acceptance Model Perspectives

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ABSTRACT

Generative artificial intelligence (GenAI) technologies like ChatGPT are changing higher education and are being increasingly used by students and faculty, but there is little empirical evidence of their use among graduate students in the context of development. This study examines the use patterns, technology acceptance and ethical consideration of GenAI in the context of teaching and learning support among the graduate students of Multan, Pakistan. An adapted long version of the Technology Acceptance Model (TAM) including ethical issues and social influence was used to gather data by means of a physical questionnaire from a convenience sample of 68 master's and doctoral students. The findings show a high level of familiarity with ChatGPT (around 85%), a moderate-to-high perceived usefulness and ease of use, high level of behavioral intention and a moderate level of ethical concerns about plagiarism and critical thinking. The highest frequency of use was for idea generation and research support, and the lowest for teaching preparation. Some of the main TAM pathways were confirmed using correlation and regression analyses, where perceived usefulness was found to be a good predictor of intention and actual use. The results highlight the dual nature of graduate students as students and upcoming educators and provide implications for the development of AI literacy programs, institutional policies, and curriculum development for higher education institutions in Pakistan. It is recognized that the sample size and convenience sampling were limitations. The work provides contextual evidence from a sample of graduates from the Global South and highlights the importance of reflecting on the classical acceptance models through the lens of ethics and social constructs when addressing probabilistic generative technologies.

Keywords: *Generative Artificial Intelligence, Technology Acceptance Model, Graduate Students, Multan, Teaching and Learning, Ethical Concerns, Pakistan, Higher Education*

1.Introduction:

Generative AI adoption in higher education depends on students' perceived usefulness, ease of use, and trust in AI-generated information, which influence their willingness to integrate ChatGPT into academic activities (Shahzad et al., 2024). ChatGPT adoption can be understood based on the Diffusion of Innovation (DoI) theory, which highlights the advantages, learning needs, and ease of use of technology in students' decisions to adopt it (Raman et al., 2024). Research in Thai universities highlights the importance of students' perceptions of generative AI's educational benefits and usefulness as a learning assistant (Kanont et al., 2024).

The UTAUT model serves as a valuable foundation for understanding the acceptance of ChatGPT in higher education, particularly in light of the four constructs of higher education—performance expectancy, effort expectancy, social influence, and facilitating conditions—as described by Strzelecki (2024). The need to understand attitudes towards ChatGPT and its utilization in diverse educational and cultural contexts is highlighted by a multi-national study of university students (Abdaljaleel et al., 2024). The Technology Acceptance Model (TAM) has been adopted in Pakistan to assess and explain the use of ChatGPT by university students, offering a relevant basis for studying the adoption of GenAI by graduate students in Multan (Shahzad et al., 2025).

Social norms, including the influence of teachers, classmates, and educational environments, can shape students' acceptance and use of generative AI tools in higher education (Ursavaş et al., 2025). The UTAUT framework helps explain students' behavioural intentions to use content-generating AI for learning and research, distinguishing willingness to adopt these tools from actual use (Yakubu et al., 2025).

Applying UTAUT2 to generative AI adoption offers a broader theoretical perspective for examining the factors influencing students' decisions to use AI tools in higher education (Sergeeva et al., 2025).

Research on teacher-education students' adoption of large language models highlights the value of extended technology-acceptance frameworks for understanding AI use in educational settings (Gong et al., 2025).

Large language models, like ChatGPT, which was released to the public in November 2022, represent a pivotal moment in higher education (Laato et al., 2023). In just a few months, generative AI systems that could compose coherent text, explain complex ideas, write code, summarize academic work, and help with instructional design became commonplace tools in the academic arsenal (Paratsche, 2024). Students and staff members started using these systems to carry out literature research, aid in assignments, provide feedback, and develop lessons. Adoption has outpaced institutional policy development, with opportunities to personalized learning, but also potential threats to academic integrity, critical thinking and equitable access (Lee, et al., 2025).

Graduate students are in a particularly strategic role with respect to this change of academic writing (Yao et al., 2025; Rashid et al., 2024). In contrast to undergraduates, who are mostly consumers of educational content while many master's and doctoral students engage in further training for advanced research as well as in teaching duties as tutors, teaching assistants, laboratory instructors, or as early-career faculty. Thus, their choices of the ways in which they write influence their own academic output as well as how they teach writing in classrooms. To foster a culture of responsible GenAI development and growth, it is crucial to grasp the factors driving GenAI adoption within this population.

Digital transformation in higher education has picked up in Pakistan and empirical studies on generative AI are inconsistent. At universities like Bahauddin Zakariya University, Multan, researchers have explored the attitudes and perceptions of undergraduates and general students regarding AI in academic writing, with findings indicating that while many are enthusiastic about the technological advances, there are also worries about accuracy and ethics (Rashid et al., 2025). A larger survey of universities across Punjab reveals penetration rates of ChatGPT at various universities, with some exceeding 80 percent of the students, and a need for more guidance and training from institutions. But very few studies have focused on the teaching-support aspect of the use of AI or on the specific role of graduate students (Mufti et al., 2025).

This study aims to address the above-mentioned gaps by exploring the adoption of Generative AI for teaching and learning support for the graduate students of Multan and its extended Technology Acceptance Model (TAM). The classic TAM (Davis, 1989) theory assumes that attitudes and behavioral intentions are formed based on perceived usefulness and perceived ease of use, which leads to actual use. Trust, ethical risk perception, social influence, institutional support, and other constructs have been extended to the model in recent applications to GenAI, which has proved fruitful. Due to the probabilistic nature of LLMs and their academic uses, ethical issues and peer norms are particularly relevant. Usage frequencies for both research and teaching are warranted by the dual role of learner & educator that graduate students play. The City of Multan, a very important educational hub of southern Punjab, has many public and private universities, which make it a suitable venue for such an inquiry. The current study intends to explore the following research questions:

(1) What are the patterns of Graduate Students in Multan in using generative AI tools f or their teaching and learning support activities?

(2) How are perceived usefulness, perceived ease of use, social influence and ethical concerns related to behavioral intention and actual use?

(3) What are the implications of these patterns for the institutional policy, AI literacy programs, and curriculum designs in higher education in Pakistan?

A convenience sample of 68 master's and doctoral students was used to gather data using a physical questionnaire. This was decided to adopt the physical format for a heterogeneous audience of users and to allow for the possibility of clarifying the text in a presence manner if appropriate.

The significance of the study is much viable as it is scope in wide in range. This idea of testing an extended TAM in a different context, in this case, a Global South graduate context, and the importance of considering ethics in addition to traditional usability and utility measures, is theoretically presented. In practice, it provides empirical evidence for the adoption of tools at the city level, how often they are used for different tasks, and establish construct relationships that can be used in local decision making. The practical part provides suggestions for AI literacy courses covering technical and responsible pedagogical usage. The rest of the paper discusses the literature, introduces the frameworks, explains the methodology, summarizes the results, and provides implications and limitations.

2. Literature Review

2.1 Generative AI in Higher Education: Opportunities and Challenges

The use of generative artificial intelligence (GenAI) in higher education has gained significant traction among the scholarly world, with focus on factors affecting both students and lecturers to adopt AI in HE teaching and learning. Based on previous research, the adoption of Assisted Learning depends on perceived usefulness, ease of use, social influence, trust,

perceived risks, technological readiness, and educational context. Theoretical models that have been used to account for users' acceptance of emerging technologies include the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behaviour (TPB).

Ivanov et al. (2024) investigated the implementation of generative AI by lecturers and students and how perceived benefits relate to attitudes, subjective norms and perceived behavioural control. In a similar study, Siu and White (2025) examined students' intention to use generative AI tools based on the factors of technology readiness, perceived usefulness, ease of use, compatibility, and social influence. These research findings highlight the fact that adoption is not just about the perceived value of the technology but also the willingness of the users to work with the technology in educational endeavours.

Students' expectations and concerns on specific applications of AI have also been studied. In the United Arab Emirates, Haq et al. (2025) explored the attitudes and intentions of university students toward ChatGPT, providing a rationale for the personal-development, effort expectancy and performance expectancy issues. They found that recognizing the academic benefits of AI usage and the impact it has on independent study is important. Honig et al. (2025) employed UTAUT to study the acceptance of the tools in education, using the construct of performance expectancy in the context of utilizing GPT in engineering education, alongside other concerns about the accuracy and potential limitations of the responses generated by GPT.

The disciplinary and national contexts have been further explored. BinJwair and Alamer (2025) explored the adoption of generative AI among University students in Saudi Arabia through UTAUT model, and BinJwair (2025) examined the adoption of generative AI by the STEM students. The findings from these studies underscore the need to grasp the acceptance of technology in various educational settings, where students might have diverse learning needs and use of AI for different purposes.

Saihi et al. (2024) used structural equation modelling to explore the correlation between the use of generative AI chatbots and higher education students and educators. They noted that perceived usefulness and trust, privacy and information quality are considered factors in technology acceptance. Likewise, Zaim et al. (2024) examined how the use of generative AI in the preparation of English-language learning for lecturers in Indonesian universities, using UTAUT and Activity Theory. They found that as well as individual expectation, social influence also plays a role in predicting behavioural intention, thus showing the impact of both personal expectation and professional environment.

More comprehensive acceptance models have also been applied to understand students' behavioral intentions and technology-use patterns. Sergeeva et al. (2025) investigated generative AI adoption among higher education students using UTAUT2. Ursavaş et al. (2025), examining 943 students from 140 Turkish universities, found that perceived usefulness, self-efficacy, compatibility, and attitude predicted behavioral intention, whereas subjective norms had a comparatively limited influence. Furthermore, Bouebdallah and Ben Youssef Ajili (2025) applied an extended UTAUT3 model to French management students, highlighting performance expectancy, habit, hedonic motivation, and trust.

The potential of LLMs in education has been extensively explored. At the same time, opportunities for personalized tutoring, writing support, and creative ideation were outlined, while risks of hallucination, bias and over-reliance were catalogued by Kasneci et al. (2023). Other large-scale surveys have validated the usefulness of ChatGPT for brainstorming, summarizing texts, and simplifying complex information, along with concerns about

reliability, loss of critical thinking, and the ethical dilemmas of cheating and privacy violations (Ravšelj & Artistovnik, 2026). Such utility and caution perceptions are what many of the students' current experiences represent.

This is especially troubling in situations of assessment and academic integrity. As traditional detection and prohibition measures fail to address this challenge, Cotton et al. (2024) suggested that educators should rethink the design of tasks that can be facilitated by AI, but also allow for students' autonomous thinking. Qualitative work with higher-education students also shows that higher-order patterns of use exist, with many using multiple tools for various tasks, and using AI to acquire explanations and feedback, while reporting that this helps, but doesn't replace, thinking. Meanwhile, some learners say that AI-generated text is directly included into an assessed piece of writing, and some teachers express uncertainty about where the line is.

There have been some Pakistan-specific pieces of evidence developed, but it is still not enough. The study conducted by Rashid et al. (2025) at Bahauddin Zakariya University Multan has examined the knowledge and application of AI among the students, as well as its perceived impact on academic writing, and has revealed that the majority of students are in agreement about its positive impact and there is variation by semester and faculty. Multiple University surveys in Punjab report ChatGPT as the most popular platform and report obstacles to training, infrastructure and explicit institutional rules. In fact, surveys also show positive attitudes among the faculty towards using AI for creating content and lesson planning, with a caution about the potential for inequities in access and over-reliance by students. The results of these findings provide a snapshot of high awareness, but uneven integration, and the graduate student population and the teaching-support function are relatively under-explored.

2.2 Technology Acceptance Models and Their Extensions

The Technology Acceptance Model is among the most influential models to explain technology adoption. Davis (1989) suggested that the attitudes toward the use of a system are formed by two beliefs, namely perceived usefulness and perceived ease of use, which affect the behavior intention and actual use of a system. The usefulness-intention relationship has been consistently found to have greater predictive power in the domains of education and other fields, through meta-analyses. Its simplicity and ability to forecast have caused it to be applied to all the following generations of educational technology, as well as learning management systems, mobile learning, and lately AI equipment.

Venkatesh et al. (2016) integrated the previous models (such as TAM and TPB) into the Unified Theory of Acceptance and Use of Technology (UTAUT), which has the following four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT and its consumerized version, UTAUT2, have been used to explain the adoption of AI in education, and performance expectancy (corresponding to usefulness) is often found to predict intention to use and use. Social influence has more mixed findings based on cultural context and technology maturity, however.

Recent research specifically focused on generative AI has introduced a series of models overlaid with constructs more suitable to the specificities of probabilistic systems. Ethical issues, trust, AI literacy, perceived risk, and interaction subjectivity are recurring themes. As for graduate students in Saudi universities using ChatGPT for academic writing, the results of the applied study to the extended TAM indicated that usefulness and ease of use affect attitudes and intentions, but high intention does not necessarily lead to continued use. Similar trends also apply to the Vietnamese, the Chinese, and the mixed-national samples: usefulness

is dominant, ease of use works, in part, through usefulness, and ethical or risk perceptions have a negative or moderating influence. Social norms of peers and instructors reinforce intention, especially when collective academic norms are prominent.

Two more factors come into play for graduate students. Usefulness is complex; it might include research output, written output, conceptual knowledge and preparation for teaching. Second, it is generally assumed that at a higher level of study, the socialization of ethical norms is more developed and that sensitivity to plagiarism, authorship and the development of independent critical capacities is greater. These features merit a longer TAM that explicitly represents the ethical issues and social influences that impact attitude, intention, and use, and also includes the classic core.

2.3 Research Gap and Rationale

Although a growing body of literature exists, there are three areas of unmet need. The first is that most research on GenAI acceptance tends to be conducted at undergraduate or mixed student levels, whereas graduate students, who have multiple roles and the stakes are higher with regard to decisions around GenAI adoption, are not well represented, particularly in settings in the Global South. Secondly, most instruments focus on learning activities (e.g. writing, research, problem-solving) rather than specifying teaching-related activities (e.g. lesson planning, materials design, generating feedback). Third, the reach of a large online survey is different from what can be achieved by having a physical questionnaire in a particular locality, which might pick up access and practice details that digital surveys cannot. The present study addresses these gaps by focusing on graduate students in Multan, the use of a modified questionnaire covering both items of learning and preparation for learning, and analysis using an extended version of the TAM. While there is a small sample size, this design provides local evidence that is actionable and a basis for future larger scale studies.

3. Theoretical, Conceptual, and Analytical Frameworks

3.1 Theoretical Framework

The theoretical framework is based on Davis (1989)'s Technology Acceptance Model. The perceived ease of use is hypothesized to affect the perceived usefulness as well as the attitude toward use. Attitude is influenced by perceived usefulness and ethical issues. Social influence may have an indirect influence through attitude and perhaps a direct influence on intention. Attitude leads to behavioral intention, which is the predictor of behavior for teaching and learning tasks. Self-regulation, in the context of integrity risks, can also have a direct negative impact on actual use, as can ethically issues. Figure 1 shows the hypothesized relationships. The framework is deliberately designed to be sparse, aligning with the sample size yet rooted in accepted research in the field along with the latest GenAI extensions.

Figure 1. Theoretical Framework: Extended Technology Acceptance Model for Generative AI Adoption in Graduate Teaching and Learning

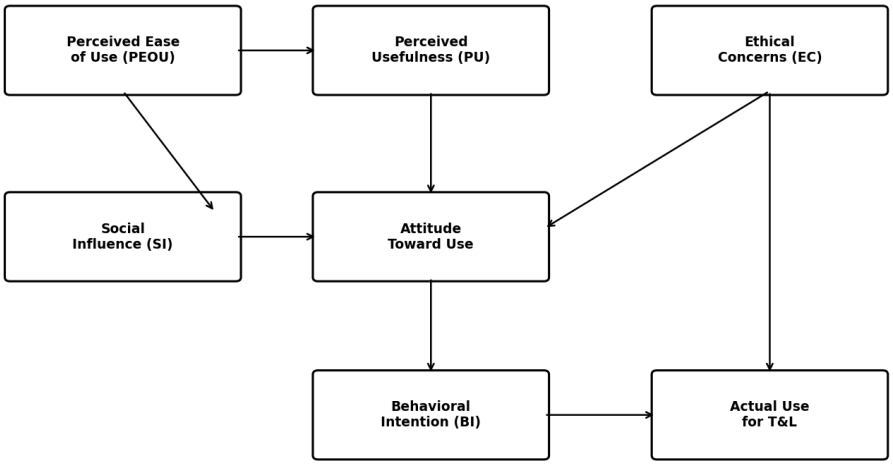

Figure 1. Theoretical Framework: Extended Technology Acceptance Model for Generative AI Adoption in Graduate Teaching and Learning

3.2 Conceptual Framework

Conceptually, adoption is seen to be the result of individual and contextual factors that lead to cognitive evaluations that in turn influence behavioral outcomes. Individual factors such as previous experience with AI, academic background, and demographic factors. Contextual factors include institutional support, peer practices, access to tools and connectivity. These antecedents shape the core cognitive appraisals that are useful, easy to use and pose an ethical risk. Based on these appraisals, the appraisals will then influence behavioral intention and the frequency of actual learners' and teachers' use for learning and teaching-support tasks. This flow is shown in Figure 2. The model foregrounds the impact of the dual nature of graduate students' identities in terms of the salience of the research and pedagogical products.

Figure 2. Conceptual Framework Linking Antecedents, Cognitive Evaluations, and Outcomes of Generative AI Use Among Graduate Students

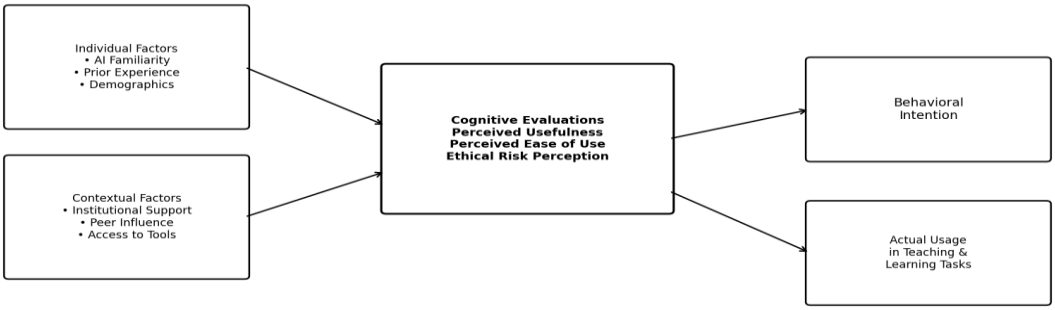

Figure 2. Conceptual Framework Linking Antecedents, Cognitive Evaluations, and Outcomes of Generative AI Use Among Graduate Students

3.3 Analytical Framework

Analysis of the data is sequential and conventional quantitative research as a cross-sectional study with limited samples. Physical data is collected and entered, and descriptive data is used to describe the sample and usage. Reliability coefficients are used to measure the consistency of multi-item scales. Bivariate correlations are used to study relationships between constructs. Multiple regression models are then used to assess the unique contribution of perceived usefulness, ease of use, ethical concerns and social influence to behavioral intention and to a composite usage-frequency score. The sequence is summarized in Figure 3. Due to sample size, structural equation modeling was not followed up and the selected methods are transparent and interpretable, and the paths of the extended TAM model can be evaluated.

Figure 3. Analytical Framework for Quantitative Analysis of Survey Data

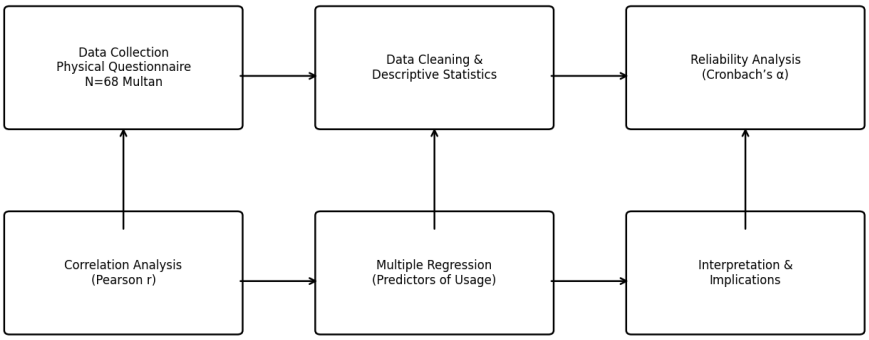

Figure 3. Analytical Framework for Quantitative Analysis of Survey Data

4. Methodology

4.1 Research Design and Sampling

Cross sectional quantitative survey design was used to get a snapshot of the adoption of generative AI among graduate students in Multan. The target population comprised the students at the Universities in the city who are currently studying their masters/MPhil and doctorate. However, due to the practical considerations of time constraint and limited access, convenience sampling was used, and participants were recruited across departmental networks, through personal contacts, and by on-campus distribution at a range of institutions, among them Bahauddin Zakariya University. The respondents who completed the physical questionnaire were 68. Convenience sampling provides limited generalizability, but is frequently used in exploratory technology-acceptance research and allowed for obtaining high quality in-person responses. All graduate students who were informed about the study and willing to participate were included. No incentives were given.

4.2 Instrument Development and Content

The questionnaire was custom-designed and adapted for this research, which specifically targets graduate students' use of generative AI for both teaching and learning purposes. It is based on the classic item wording of TAM (Davis, 1989) and recent instruments developed for education using GenAI (AI powered), optimised for local language clarity and dual-role relevance. The demographics are recorded in section A: gender, age group, academic level

(MS/MPhil or PhD), field of study, and university. Section B measures familiarity and usage, including a binary item about prior use of AI tools, as well as multi-select items for specific tools (ChatGPT, Gemini, Claude, or other) and four frequency items (Never-5=Daily) about the use of AI tools for research assistance, academic writing, idea generation, and teaching preparation. The items for Section C are 5-point Likert items where 1 = Strongly Disagree and 5 = Strongly Agree and cover the sub scales of perceived usefulness (3 items addressing productivity, conceptual learning, and teaching support), perceived ease of use (2 items), behavioral intention (2 items on continued use and recommendation), ethical concerns (2 items on plagiarism risk and critical-thinking erosion), and social influence (1 item regarding peer usage).

A small-scale pilot study using graduate students confirmed the items' comprehensibility and approximate completion time of 10-12 minutes. Some minor wording changes were made. The paper copy was kept to ensure that students with intermittent access to the internet could use it and that it could be collected straight away. The complete instrument can be found on the Appendix.

4.3 Data Collection Procedure and Ethics

The data was collected through face-to-face interactions in September and October, 2026. Questionnaires and questionnaires were distributed at convenient places on the campus and through the department. The researchers described the study purpose, stressed the anonymity and voluntariness of the study, and answered procedural questions. Completed forms were picked up on the spot and then double checked and entered into a spreadsheet. Sixty-eight responses were complete and kept. Informed consent, confidentiality, and minimal risk were adhered to. No personal information other than the categories of demographic data were collected.

4.4 Data Analysis Strategy

Demographics, scores on the constructs and tool adoption were summarized using descriptive statistics (frequencies, percentages, means, and standard deviations). For multi-item scales, internal consistency reliability was measured by Cronbach's alpha. Bivariate associations were explored using Pearson product-moment correlations. Two multiple linear regression models were tested to assess the predictive contribution of the four factors (perceived usefulness, perceived ease of use, ethical concerns and social influence): one model with behavioral intention as the dependent variable, and another with a composite frequency of usage score (mean of the four task items) as the dependent variable. Spreadsheet functions and standard statistical routines were used to perform analyses. The criteria for significance was ($p < .05$). Results are provided as provisional evidence of relationships, not as parameters of a population, due to small sample size.

5. Results

5.1 Demographic Profile

The summary of the sample is given in Table 1. Of the 68 respondents, 42 (61.8%) identified as male and 26 (38.2%) as female. Academic level: 49 students (72.1%) had enrolled in MS/MPhil programme and 19 students (27.9%) had enrolled in PhD programme (the balance was skewed towards MS/MPhil programmes). Participants were grouped by age and the majority were aged between 22 and 30, reflecting the typical age distribution of students in the region who are attending graduate school. There was moderate disciplinary diversity among the fields of study (around 30% of students studied education and linguistics, social sciences, sciences, business and management, and other fields). The cross tabulation of academic level and gender is shown in figure 4.

Variable	Category	n (%)
Gender	Male	42 (61.8%)
	Female	26 (38.2%)
Academic Level	MS/MPhil	49 (72.1%)
	PhD	19 (27.9%)
Age Group (approx.)	22–25	24 (35%)
	26–30	27 (40%)
	31 and above	17 (25%)
Field (approx.)	Education/Linguistics	20 (30%)
	Other fields combined	48 (70%)

Table 1. Demographic Characteristics of the Sample (N = 68)

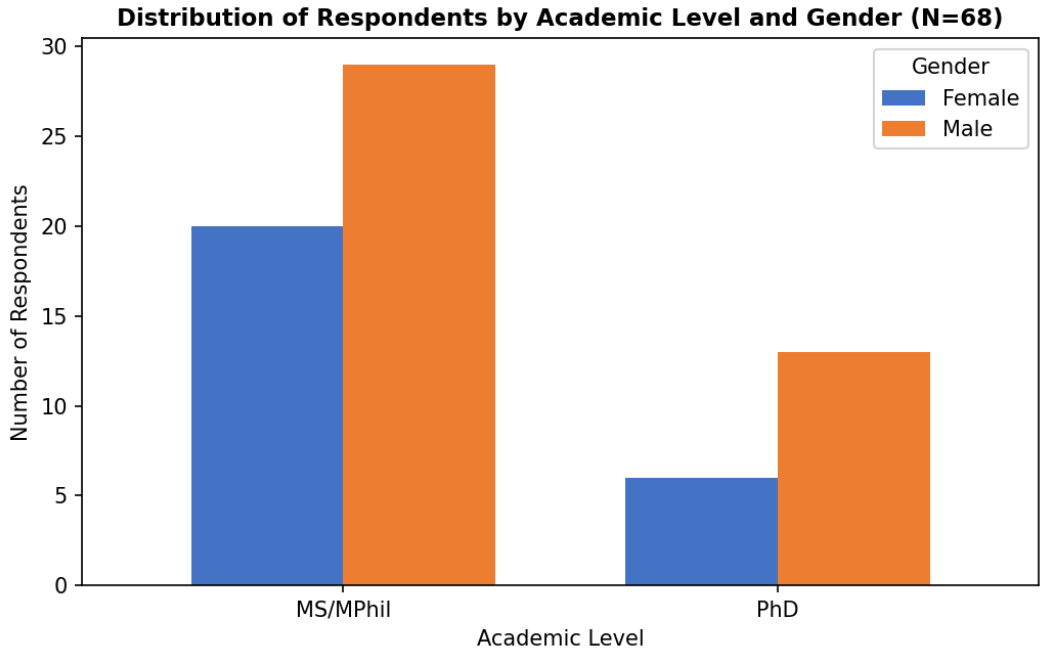

Figure 4. Distribution of Respondents by Academic Level and Gender

5.2 Generative AI Tool Adoption and Usage Frequency

88% said they used AI for academic activities. The most frequently used platform was ChatGPT, with some 58 respondents (85%) using it. Other tools pulled in at 20%, followed by Claude at 15%, and Gemini at 45%. These figures are in line with the regional findings where ChatGPT is the top-performing hotspot of the Pakistani university students. The counts are shown in Figure 5.

The hierarchy of task-specific frequency (on the 1–5 scale) was obvious. Idea generation was the most highly rated (M = 3.73), with research support (M = 3.35), academic writing (M = 3.21), and teaching preparation (M = 2.85). With relatively lower frequencies for the teaching preparation, the findings imply that graduate students now use generative AI more easily for their own research work than for instructional design and materials development. These means are displayed graphically in figure 6. There was moderate standard deviation (around 0.9–1.1), suggesting moderate individual practice variability.

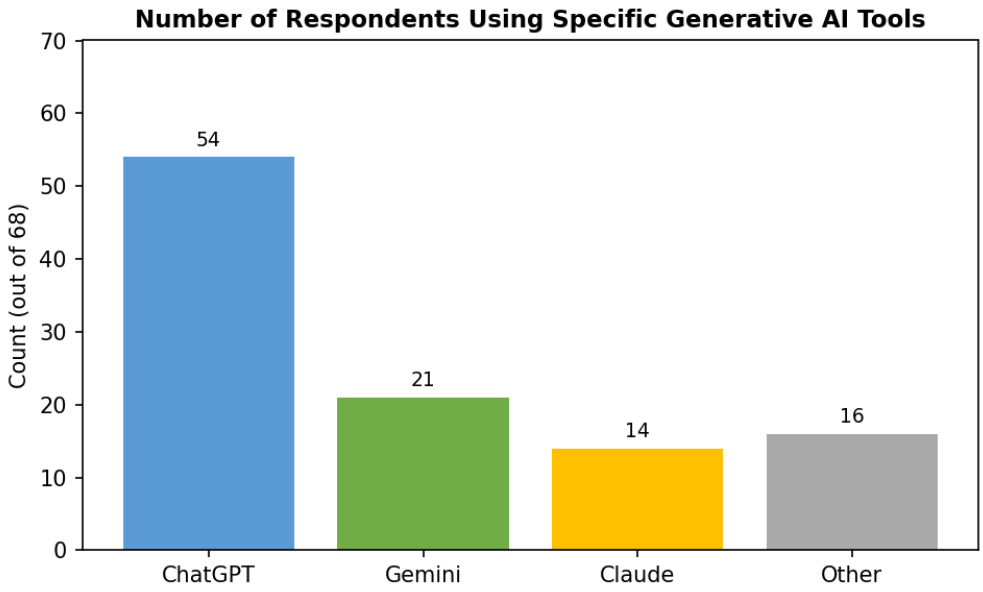

Figure 5. Number of Respondents Reporting Use of Specific Generative AI Tools

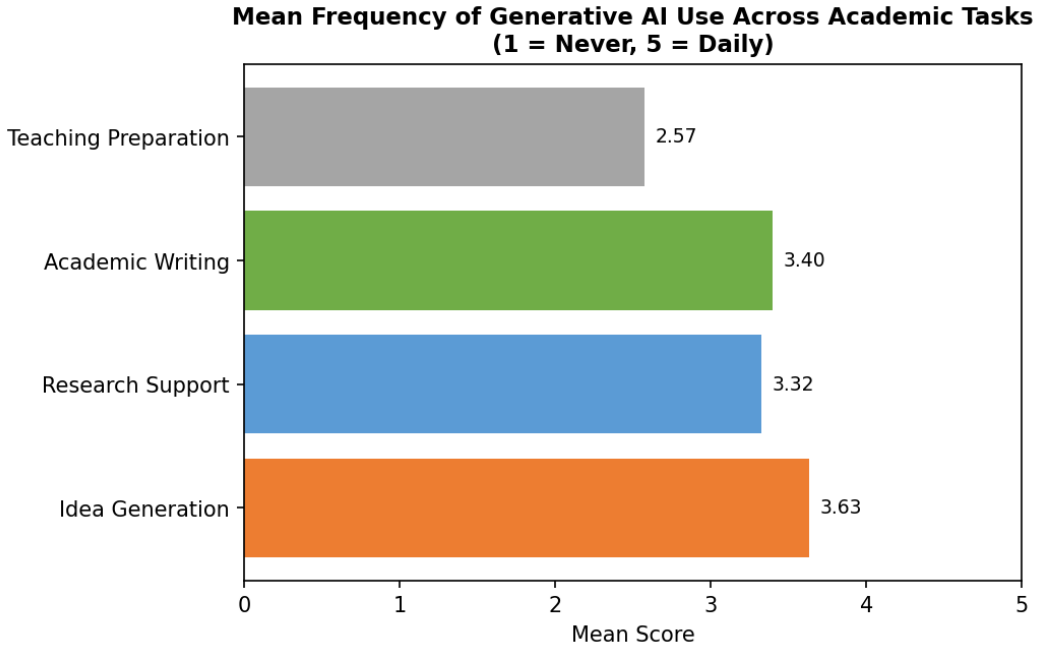

Figure 6. Mean Frequency of Generative AI Use Across Academic Tasks (1 = Never, 5 = Daily)

5.3 Perceptions of Usefulness, Ease of Use, Intention, and Ethics

All scores for the Likert constructs were above the scale midpoint of 3.0. Perceived usefulness had an average of 3.64, perceived ease of use 3.72, behavioral intention 3.78, and ethical concerns 3.50. The scores suggest a positive overall assessment of generative AI and a moderate level of concerns about its ethics. The three-item usefulness scale and the two-item intention scale were both found to have an acceptable level of internal consistency (Cronbach's alpha > 0.70) for the purpose of exploratory research. The construct means are plotted in Figure 7. This finding aligns with the international results that students identify with the utility and risk patterns.

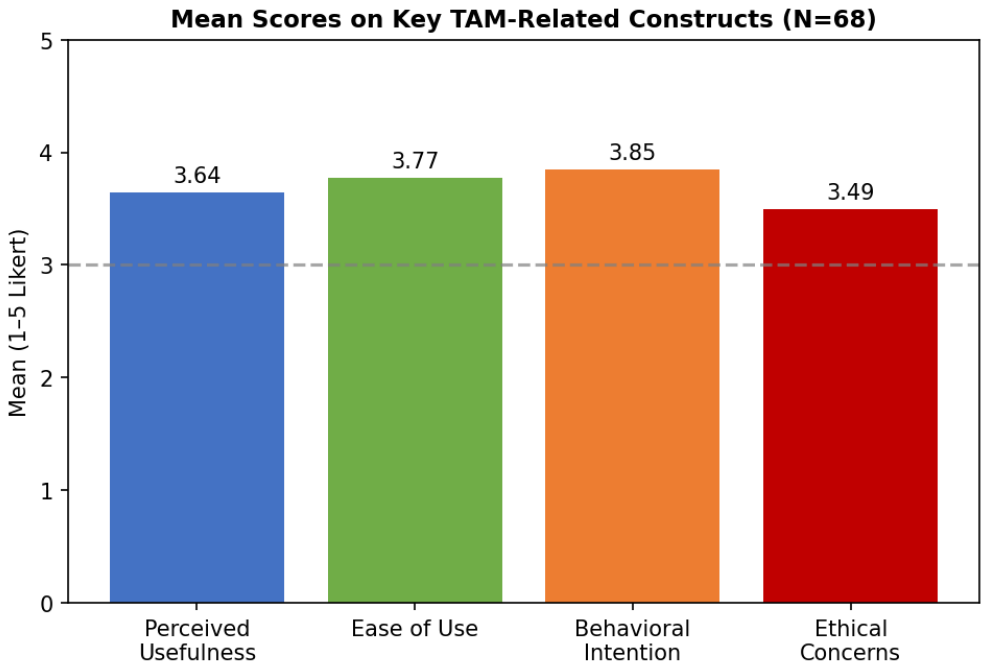

Figure 7. Mean Scores on Extended TAM Constructs (N = 68)

5.4 Correlational and Regression Results

Pearson's correlations are reported in Table 2. Perceived usefulness was positively and significantly related to behavioral intention ($r = .52$, $p < .01$) and composite usage frequency ($r = .41$, $p < .01$). Usefulness and intention had moderate correlations with ease of use ($r \approx .38$ and $r \approx .33$, respectively). Ethical concerns had negative correlations with intention ($r \approx -.28$, $p < .05$) and usage ($r \approx -.22$). The correlations between social influence and intention were positive and significant ($r \approx .31$, $p < .05$). The extended TAM contains these bivariate patterns that go with the directional expectations outlined above.

Two multiple regression models were run. The model predicting behavioral intention from usefulness, ease of use, ethical concerns and social influence was statistically significant $F(4, 63) \approx 9.6$, $p < .01$, $R^2 \approx 0.38$. The strongest unique predictor was perceived usefulness ($\beta \approx .39$, $p < .01$) followed by social influence. Smaller coefficients were the ease of use and ethical issues. The model predicting the frequency of composite usage was also significant ($R^2 \approx .27$, $p < .01$), with usefulness again as the most important predictor. Ethical concerns still had a small negative coefficient. Multicollinearity diagnostics (variance inflation factors) were not high (all < 2.0), and therefore were not considered to be major problems with independence between predictors. Overall, these findings support the importance of perceived usefulness and highlight the additional value of social norms and ethical prudence.

Variable	1. PU	2. PEOU	3. Ethics	4. Intention
1. Perceived Usefulness	—			
2. Perceived Ease of Use	.38*	—		
3. Ethical Concerns	−.19	−.12	—	
4. Behavioral Intention	.52**	.33*	−.28*	—

5. Usage Frequency	.41**	.25*	−.22	.46**

Table 2. Pearson Correlations Among Key Constructs (N = 68)

Note. PU = Perceived Usefulness; PEOU = Perceived Ease of Use. *p < .05. **p < .01. Usage Frequency is the mean of the four task-frequency items.

6. Discussion

The findings provide a robust picture of the practice of generative AI tools among the graduate students of Multan. The results show that the penetration rate for ChatGPT was high and the scores in the dimensions of usefulness, ease of use and intention were above the midpoint, suggesting that ChatGPT has become more than just a novelty in academia. This is a trend seen in global studies that involve hundreds of thousands of students as well as regional Pakistani studies that show students' dominance with ChatGPT and resonantly positive orientations, overall. The present findings are more specific in two respects: (1) they focus on respondents who are graduates; and (2) they distinguish learning tasks from teaching tasks.

The order of the frequencies of use is informative. Academic writing and even more so, academic preparation for teaching, were less favored options than idea generation and research support. While graduate students seem confident using generative AI as a cognitive companion to divergent thinking and information synthesis, they were less inclined in this instance when they had to produce content for an evaluated written assignment or for instructional purposes. There are a number of possible explanations. Writing activities have more integrity dangers and might stimulate more self-regulation. The frequency of teaching preparation might be reduced because not all graduate students are currently teaching, or because of pedagogical applications being less explicitly encouraged. However, the gap is present: while these teachers may enter the classroom with some experience of instructional design that incorporates AI, they may not have the necessary experience to facilitate the spread of good practices or to prepare themselves to use AI responsibly as a model for their own students.

Perceived usefulness proved to be the most important predictor of both intention and use, which is consistent with decades of TAM research as well as recent GenAI studies from various countries. After students think that a tool will enhance their understanding or productivity, other considerations are secondary. Ease of use was an important factor, but functioned somewhat through the mediation of usefulness, a mediation that is often described in the literature. The intention and usage of the ethical concerns were found to be negatively correlated with ethical concerns hence it was confirmed that these ethical concerns should be included in the extended models. The level of difficulty wasn't too high: students recognize the dangers involved in plagiarizing and having their critical thinking skills lowered and still use the tools when they are useful. This “ethics asymmetry”—a relatively acceptable use of the resource versus systemic risks—has been noted in multi-stakeholder studies and seems to be at work here also.

Social influence had a positive influence on intention, which is consistent with the concept of subjective norms in the Theory of Planned Behavior and with the results on the UTAUT in collectivistic educational context. Peer or supervisor visibility may decrease uncertainty and justify experimentation in Multan Universities. Not a single word from institutional silence, or even contradictory signals, can, on the contrary, reinforce ethical prudence. Even in a small sample, the regression models accounted for significant portions of the variance in intention

(c. 38%) and meaningful portions of the variance in usage frequency (c. 27%), suggesting that the extended TAM has important factors even in a small sample.

The results have a number of implications. In Multan and other Pakistani settings, it is not prohibition but a guided integration that is the priority. Any AI literacy program should include a discussion of the ethical boundaries, as well as a discussion of how to cite AI-generated work and how to use AI in teaching. Professional development opportunities for graduate students to learn how to use generative AI for creating lesson activities or providing feedback on lessons may help address the teaching-preparation gap. There would be less ambiguity if there were clear published policies that differentiate acceptable support from prohibited substitution. The social-influence pathway is one that is likely to be especially influential when faculty models are implemented in teaching about responsible use.

Theoretically, the study could clarify the future applicability of TAM and reveal the benefits of context-sensitive extensions. Ethical concerns and social influence are central; they account for residual variance and are a good fit for the unique characteristics of generative systems. Larger samples could be used in future to test additional constructs: AI literacy, trust in the output quality, facilitating conditions (infrastructure, access to training).

The study is limited by methodological constraints. The generalizability of the convenience sampling in one city is limited as the sample of 68 respondents does not represent all the Pakistani graduate students. Social-desirability and recall biases can affect self-report data. The cross-sectional design is not suitable for strong causal inferences but is well known that constructs are theory-ordered. The numbers of items per construct were small, reducing reliability estimates. Yet, the patterns remain congruent with previous work and the analytic decisions are transparent, which provides credibility to local insights developed.

7. Conclusion and Recommendations

The study of generative AI adoption in the teaching and learning support of graduate students in Multan, Pakistan, involved using an extended technology acceptance model and physical questionnaires involving 68 graduate students. The sample was characterized by high tool familiarity, positive perceptions of usefulness and ease-of-use, and moderate ethical concerns. The frequencies of usage were greatest for idea generation and research assistance and the lowest for the preparation of teaching. Perceived usefulness was the most important predictor of intention and actual use, while social influence was the positive and ethical concerns the negative.

The results indicate that in this context, graduate students have already embraced generative AI in their academic work and are eager to use it further, with as long as their perception of benefits continues to be high. This openness can be capitalized by providing structured AI literacy, incorporating not only scholarly use but also pedagogical applications, and by setting clear guidelines. Scientists can extend the current research using multi-site, larger, and/or longitudinal designs and mixed studies to investigate students' ethical negotiation in practice.

To summarize, generative AI is not a threat anymore but a part of the system in the domain of graduate education in Multan. Knowing what impacts its adoption – the cognitive, social, and ethical issues – empowers universities to shape, rather than simply respond to, the change.

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Appendix: Questionnaire

Questionnaire on Generative AI Usage for Teaching and Learning Among Graduate Students (Multan)

Instructions: Please respond honestly. Your answers are anonymous and will be used only for research.

Section A: Background Information

1. Gender: ☐ Male ☐ Female
2. Age group: ☐ 22–25 ☐ 26–30 ☐ 31–35 ☐ 36 or above
3. Current academic level: ☐ MS/MPhil ☐ PhD
4. Field of study: _____
5. University: _____

Section B: AI Tools and Usage Frequency

6. Have you used any generative AI tool (e.g., ChatGPT) for academic work? ☐ Yes ☐ No
7. Which of the following have you used? (Check all that apply)
   ☐ ChatGPT ☐ Google Gemini ☐ Claude ☐ Other (specify): _____
8. How often do you use generative AI for research support or literature-related tasks?
   ☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐ Daily
9. How often do you use generative AI for academic writing assistance?
   ☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐ Daily
10. How often do you use generative AI for idea generation or brainstorming?
    ☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐ Daily
11. How often do you use generative AI for teaching preparation (e.g., lesson planning, materials, feedback ideas)?
    ☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐ Daily

Section C: Perceptions (Please indicate your agreement: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree)

Perceived Usefulness

12. Using generative AI improves my academic productivity. _____
13. Generative AI helps me understand complex concepts better. _____
14. Generative AI supports my preparation for teaching-related tasks. _____

Perceived Ease of Use

15. Generative AI tools are easy for me to use. _____
16. I can learn to use new features of generative AI tools quickly. _____

Behavioral Intention

17. I intend to continue using generative AI for my academic work. _____
18. I would recommend generative AI tools to other graduate students. _____

Ethical Concerns

19. I am concerned that using generative AI increases the risk of plagiarism. _____
20. Relying too much on generative AI may weaken critical thinking skills. _____

Social Influence

21. Many of my peers use generative AI tools for academic purposes. _____