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ADOPTION READINESS AND PERCEIVED RELIABILITY OF GENERATIVE AI TOOLS IN SOFTWARE DEVELOPMENT EDUCATION

Aimah Bilal
BSCS ,Air University Multan Campus, Islamabad
Eman Qazi
BSCS ,Air University Multan Campus, Islamabad
Amna Noor
BSCS ,Air University Multan Campus, Islamabad
Abdul Moiz
BSCS ,Air University Multan Campus, Islamabad
Dr. Muhammad Arfan Lodhi*
Higher Education Department, Punjab
Email: samaritan_as@hotmail.com
***Corresponding Author**
Dr. Muhammad Arfan Lodhi
Higher Education Department, Punjab
Email: samaritan_as@hotmail.com

Abstract

Large Language Models (LLMs) and Generative Artificial Intelligence (GenAI) have proliferated so quickly that they have caused a revolution in computer science and software engineering education. The adoption readiness and perceived dependability of GenAI technologies, like GitHub Copilot and ChatGPT, among undergraduate students in an emerging educational ecosystem are examined in this study. This study states about all the aspects of how AI usage is impacting the software development. The current discrepancy between the high frequency of ad hoc student usage and the serious ethical and technical hazards noted in growing literature, together with the absence of formal institutional frameworks, serves as the foundation for this study. Data was gathered from a stratified sample of 150 undergraduate students in universities over several semesters and skill levels using a quantitative descriptive survey design. The study integrates aspects of perceived reliability and trust using an enhanced Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm. It takes a proper look at the revolution caused in software engineering by the usage of AI. The findings show that although Effort Expectancy and Performance Expectancy are the main factors influencing adoption, there is still a significant "reliability gap" where students express doubts about the veracity of intricate logical outputs. The results similarly show a favourable correlation between perceived performance gains and the use of structured AI, but they also raise serious worries about "hallucinations" and security flaws in AI-generated code. The findings are properly analysed to see how and what impact is brought on the education by the integration of AI. In order to prevent the creation of new digital divisions, the study suggests that successful integration necessitates a shift from syntax-focused courses to logic-driven verification models, backed by open institutional policies and strong AI literacy initiatives.

Keywords: Technology-Enhanced Learning; AI Coding Assistants; Software Development Education; UTAUT; Perceived Reliability; Higher Education

1. Introduction

A fundamental paradigm shift in computer science and software engineering education has been brought about by the explosive growth of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs). The educational landscape has evolved from typical static toolsets to an interactive setting where AI serves as a "quasi-social partner" in the learning process since ChatGPT's public release (Nikolaidis, et al., 2024). This has caused less interactivity of students towards education and learning process as it is seen that they find these tools as shortcut for performing tasks. This change is not just technological but also educational because it challenges conventional approaches to teaching programming grammar and necessitates a reassessment of how students absorb logical structures.

The "reliability-utility paradox," which weighs the hazards of technological debt and semantic "hallucinations" against the enormous productivity increases provided by tools like GitHub Copilot, is crucial to this change. These tools help a lot if used to learn and seek guidance for different fields and tasks but it is seen that students are using them more for their ease and shortcuts towards hard work. Empirical research indicates that over dependence on these technologies can result in "cognitive offloading," potentially undermining critical thinking and autonomous problem-solving abilities, despite the fact that students frequently report enhanced efficiency and less cognitive load (Evangelista, 2024). The integration of these probabilistic systems requires a change in the student's role from a code synthesizer to a critical verifier of automated outputs in software development education, where underlying logic is crucial.

Student adoption has quickly surpassed official academic policy, and this shift is taking place within a complicated institutional structure. There is a pressing need to close the gap between ad hoc student usage and structured, ethical integration in developing educational ecosystems like Pakistan, where the Higher Education Commission (HEC) just started requiring AI literacy courses (Daniel López-Fernández, 2025). These courses will help a lot as if they make students learn how to use AI for their learning and smart work instead of running from the learning it would bring a big change. Designing a curriculum that maintains academic integrity while preparing graduates for an increasingly AI-native professional environment requires an understanding of adoption readiness, particularly how students calibrate their faith in AI reliability (Hanan Alotaibi, 2025).

1.1 Background of the Study

Many academics refer to the rise of Generative Artificial Intelligence (GenAI) as a "major upheaval" in computer science (Cigdem Sengul, 2024). With 100 million users in its initial two months of operation, ChatGPT's adoption rate of conversational agents and big language models has outpaced nearly all prior technical innovations since its launch in late 2022 (Cigdem Sengul, 2024). This phenomenon has evolved from a peripheral convenience to a key element of the student experience in the context of software development education. GenAI is being used to make vibe coding easier that helps in software development. According to current industry data, 85% of software engineering professionals will use GenAI by 2026. This means that today's students are entering a field where AI-assisted programming is expected (Görkem Giray, 2026).

This global trend is particularly impactful in higher education settings, where the jump in AI usage has been reported to move from 53% in 2024 to an estimated 88% by 2025 (Jiang Xiaomin, 2025). The mechanism of this adoption is driven not only by the convenience of auto-filling standard code but also by the promise of reducing cycle time and providing cognitive support for brainstorming and problem-solving (Görkem Giray, 2026). This has helped us in brainstorming and while reducing time to do coding and work accordingly, also this works in ways that has helped us in many ways. Unlike traditional educational tools, GenAI functions as a "quasi-social partner," leveraging anthropomorphic interfaces that foster a sense of "perceived comfort" and interactive fluency among students (Alexander Bick, 2025). We have observed many advantages of GenAI as well as the disadvantages but it is also observed that it helps a lot in working making it easier and less time consuming. Recent studies confirm that

GenAI is being used for a broad range of tasks, including creating study hypotheses, generating boilerplate code, and providing immediate feedback on drafts (Hanan Alotaibi, 2025).

The current literature landscape offers several critical perspectives on this shift. They are observed that how and where it is affecting in what ways. First, the speed of adoption for GenAI at work and home has been documented as faster than both the personal computer and the internet (Kaur, 2025). Second, empirical evidence suggests that while these tools provide significant productivity gains, they also introduce technical debt and replication of "buggy code patterns" (Görkem Giray, 2026). Third, the perceived reliability of these tools is highly variable; while they excel at "easy" programming tasks, their performance on complex logic remains prone to semantic errors (Lidija Weis, 2026). Fourth, academic staff in various global contexts are beginning to integrate GenAI into grading and administrative tasks, though often without standardized institutional guidance (Stephanie A. Besser, 2026). Finally, in specific developing contexts like Pakistan, there is a recognized "policy laggardness," where student enthusiasm for AI tools is not yet matched by institutional training or ethical regulation (Yin, 2026).

1.2 Statement of the Problem

Despite the widespread adoption of tools like ChatGPT and GitHub Copilot, there exists a significant research gap regarding the "readiness" of the academic ecosystem to support this transition responsibly. In many regions, particularly within the Pakistani higher education landscape, the implementation of AI has been largely unregulated, resulting in a widening divide between individual student adoption and institutional governance (Yin, 2026). Also, we have seen students being totally dependent on AI for their working and performing any tasks. While students are using these tools to complete up to 30% of their research and coding tasks, only a minority receive formal training on the limitations and ethical implications of the technology (Neha Rani, 2026).

The primary contradiction in the current literature is the "reliability-utility paradox": students and practitioners perceive high value in GenAI for task completion, yet objective metrics indicate that over 60% of LLM-generated code may contain security vulnerabilities or fail functional requirements (Görkem Giray, 2026). This raises critical concerns for software development education. If students rely on AI for "cognitive heavy lifting" during their formative years, there is a risk of "cognitive substitution," where the student loses the ability to perform independent logical reasoning or critical evaluation (Lidija Weis, 2026). It is preferred more for students to focus on their independent logical reasoning and performing during the years of growth as if they are totally dependent on AI during these years, it is considered as they are not able to perform that well on their own afterwards. Furthermore, existing technology acceptance models often focus purely on rational utility, failing to account for the unique psychological dimensions of trust and "AI anxiety" that arise when using probabilistic systems in academic settings -There is an urgent need for survey-based evidence that captures the relationship between adoption readiness, perceived reliability, and the resulting impact on student proficiency in a context where institutional support is still evolving.

1.3 Research Questions

To address the identified gaps, we have focused on the following research questions:

1. What is the level of adoption readiness and frequency of generative AI tool usage among undergraduate computer science and software engineering students?
2. How do students perceive the reliability and accuracy of code generated by AI tools, and what specific factors influence their level of trust?
3. Is there a significant relationship between the frequency of AI tool usage and students' perceived improvement in programming skills and academic performance?

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1.4 Conceptual Framework

The concept map illustrates AI as the central driving force in contemporary computer science education, influencing multiple interconnected dimensions of teaching, learning, and academic development. At the core, AI tools function as intelligent educational assistants that support students in coding, problem-solving, content generation, feedback, and personalized learning. Their integration is not isolated but extends across several educational outcomes and perceptions. The model suggests that students' adoption readiness plays a crucial role in determining whether AI technologies are embraced within the learning environment. Learners who possess technological confidence, digital literacy, and openness to innovation are more likely to integrate AI tools into their academic activities. Once adopted, the frequency of usage becomes a significant factor, as regular interaction with AI systems enhances familiarity, efficiency, and dependence on these technologies for educational tasks.

The effectiveness of AI is further shaped by students' perceptions of reliability and accuracy. When learners view AI-generated responses as trustworthy, consistent, and technically correct, they are more willing to use these tools for assignments, programming tasks, and knowledge acquisition. These perceptions contribute to the development of trust**,** which serves as a foundational element connecting technological acceptance with sustained educational use. As students engage with AI tools, they experience skill improvement, particularly in programming, debugging, critical thinking, information retrieval, and problem-solving. AI-assisted learning provides immediate feedback and adaptive support, enabling learners to strengthen both technical and cognitive competencies. These improvements ultimately contribute to enhanced academic performance, reflected in better learning outcomes, increased productivity, higher-quality assignments, and improved understanding of complex computer science concepts. The interconnected structure of the concept map emphasizes that AI integration in education is a dynamic and cyclical process rather than a linear one. Adoption readiness influences usage, usage shapes perceptions of accuracy and reliability, these perceptions build trust, trust encourages continued engagement, and sustained engagement fosters skill development and academic success. Together, these elements demonstrate how AI acts as a transformative educational technology that supports student learning while reshaping the teaching and learning ecosystem within computer science education.

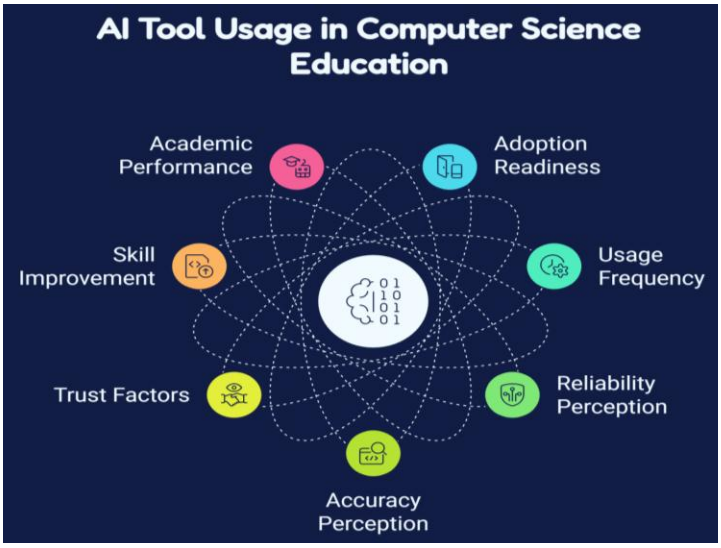

Figure 1. Conceptual Framework

1.5 Significance of the Study

The significance of this study lies in its potential to inform the urgent restructuring of computer science curricula in the age of AI. For university administrators, the findings provide a data-driven rationale for moving away from "rhetorical adoption" toward functional policy frameworks that address academic integrity and AI literacy (Olga V. Sergeeva, 2025). It has enhanced the structure of curricula as administration was concerned more on students' ability to learn hence, they added topics that enhance curricula in the age of AI. For educators, the study clarifies the transition from teaching syntax, which is now easily automated, to teaching logic-driven verification and problem decomposition (Stephanie A. Besser, 2026). By identifying the specific dimensions of the "reliability gap," this research helps stakeholders design interventions that mitigate the risks of over-dependency and ensure that students maintain the foundational skills necessary to thrive in an increasingly AI-integrated industry.

2. Review of the Related Literature

2.1 Theoretical Foundations

The investigation of how students adopt and sustain engagement with new technologies in academic settings is primarily grounded in the ***Unified Theory of Acceptance and Use of Technology (UTAUT)***, which integrates four core constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) (Olga V. Sergeeva, 2025).

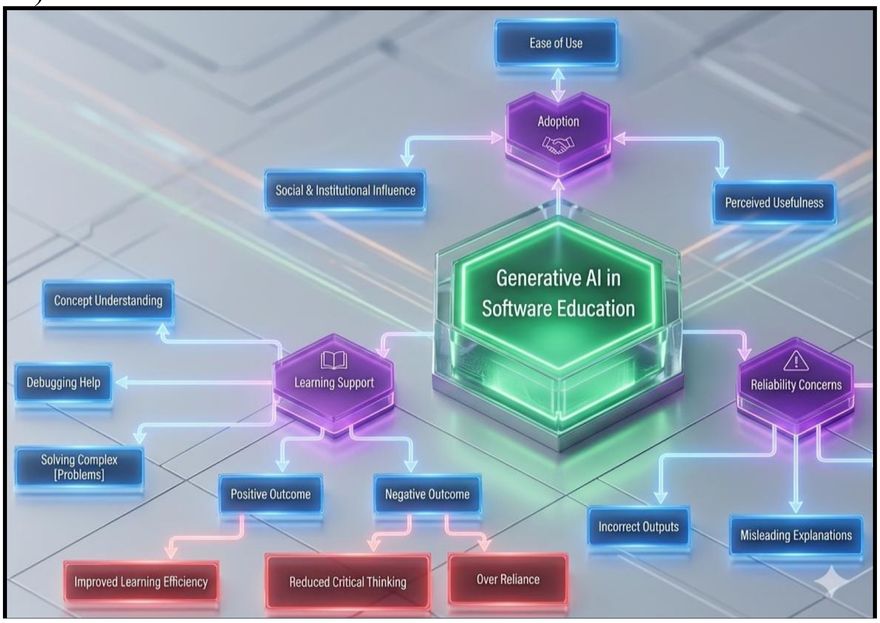

Figure 2. Mind Map - Generative AI in Software Education

Unlike earlier single-factor frameworks, UTAUT accounts for the multi-dimensional nature of technology adoption decisions, making it particularly suited for studying AI tool integration among students who face both institutional and personal motivational pressures. In the specific case of GenAI, researchers have extended UTAUT to include psychological and ethical dimensions such as "Trust," "Privacy Concerns," and "Hedonic Motivation" (Jiang Xiaomin, 2025). Performance Expectancy remains the most influential predictor of adoption intention in higher education, as students prioritize tools that offer tangible academic benefits and efficiency (Hanan Alotaibi, 2025). However, the "interactivity" of GenAI tools introduces an emotional dimension that traditional models often lack. The formation of a "quasi-social partner" relationship through anthropomorphic interfaces gives rise to variables like "perceived comfort," which can be more predictive of adoption than rational utility alone (Lidija Weis, 2026). Within the UTAUT framework, this aligns with Hedonic Motivation, the intrinsic enjoyment derived from using a tool, as a supplementary predictor that explains sustained usage beyond initial adoption. The integration of ***Media Dependency Theory*** is also relevant, as it explains how excessive reliance on AI tools can influence students' thinking and learning habits (Runna Alghazo, 2025). When students perceive AI as a primary resource for problem-solving, their internal motivation to develop independent technical competence may decline, leading to a "loss of unique voice" and potentially hindered skill (Neha Rani, 2026). This dependency dynamic is especially significant in software development education, where logical reasoning cannot be outsourced without direct consequences to professional readiness. A comprehensive theoretical framework for GenAI adoption must therefore account for the interplay between rational utility (PE, EE), social drivers (SI), and the psychological risks of cognitive dependency, all of which UTAUT's extended constructs are equipped to capture.

2.2 Review of Empirical Studies

The empirical record on GenAI in education does not present a straightforward success story, it presents a contradiction that demands careful interpretation. A systematic review of 18 studies found that purposeful AI use did yield gains in writing quality and task efficiency, yet these same studies documented significant losses in retention and independent performance when students defaulted to AI as a cognitive shortcut (Hanan Alotaibi, 2025). This is not a minor caveat; it is the central tension the field must confront. The very conditions under which AI appears most helpful, namely reducing cognitive load and accelerating output, are precisely the conditions that erode the deeper learning it is supposed to support. This contradiction sharpens considerably in the domain of software engineering, where the stakes of unreliable output are technical, not merely academic. ChatGPT and GitHub Copilot achieve reasonable accuracy on straightforward problems, at 65.2% and 46.3% respectively, but their performance degrades substantially on tasks requiring complex logical reasoning (Alexander Bick, 2025). More critically, research on the Human Eval dataset demonstrates that accuracy can collapse from 79% to 27% with sub-optimal prompting alone (Kaur, 2025). This means a student who does not already understand the problem well enough to prompt correctly will receive unreliable output, and, lacking the independent knowledge to recognize the error, may submit it anyway. Rather than bridging the competence gap, AI under these conditions widens it. The finding that Copilot increases code contributions by 6% while simultaneously raising debugging and integration overhead only reinforces this point: productivity metrics obscure a growing quality problem (Alexander Bick, 2025).

Recent literature demonstrates that the integration of artificial intelligence into higher education has moved beyond questions of accessibility and entered a phase characterized by concerns about learning quality, cognitive engagement, trust, and professional preparedness. Across diverse educational and professional contexts, researchers increasingly portray AI not merely as a technological tool but as a transformative agent reshaping how knowledge is produced, evaluated, and applied. Studies focusing on professional computing environments reveal substantial shifts in software development practices.

Görkem Giray (2026) found that AI-assisted development significantly reduces software production cycles, enabling faster completion of programming tasks. However, these efficiency gains are accompanied by increased validation overhead, as developers devote considerable time to verifying AI-generated outputs. Similarly, Besser (2026) observed a transition in professional technology roles from manual code construction toward the evaluation and critique of AI-generated artifacts. Together, these findings suggest that software development is increasingly becoming a process of supervision and validation rather than direct production.

Nevertheless, uncertainty remains regarding the long-term maintainability of AI-generated code and the competencies required for future entry-level professionals. Within educational settings, student adoption of AI technologies appears to be accelerating rapidly. Hanan Alotaibi (2025) identified performance expectancy and effort expectancy as the strongest determinants of AI acceptance among Saudi university students, indicating that learners are primarily motivated by perceived usefulness and ease of use. Jiang Xiaomin (2025) similarly reported that AI usage among Chinese university students is projected to reach exceptionally high levels, with intrinsic motivation emerging as a significant driver of adoption. These studies collectively suggest that students increasingly view AI as an essential academic resource. At the institutional level, however, Olga V. Sergeeva (2025) found that formal governance structures, faculty training initiatives, and ethical guidelines have not kept pace with student adoption rates, creating a substantial gap between technological practice and institutional preparedness.

Lodge and Loble (2026) argue that AI may foster a phenomenon they describe as false mastery, whereby students confuse successful task completion with genuine understanding. This concern is reinforced by research conducted by Hong et al. (2025), who found that students with strong prior knowledge tend to use AI as a tool for deeper exploration, whereas lower-performing students frequently employ it as a mechanism for task avoidance. The findings indicate that AI can either enhance or undermine learning depending on students' existing cognitive foundations. Extending this argument, Neha Rani (2026) observed that although GitHub Copilot increases coding productivity, it may encourage cognitive substitution, where learners rely on generated solutions rather than engaging in independent reasoning processes.

AI. Lidija Weis (2026) reported that computing students place greater importance on response consistency than on logical accuracy when evaluating AI systems. This finding suggests that students may equate confidence and coherence with correctness, potentially increasing vulnerability to misinformation and erroneous outputs. Similar concerns emerge in the work of Alshammari (2025), who emphasizes that AI literacy and transparency are essential for maintaining trust between teachers and students. Trust therefore appears to be a double-edged construct: while it facilitates adoption and engagement, excessive or misplaced trust may weaken critical evaluation skills and reduce scrutiny of AI-generated content. The tension between assistance and dependency is also evident in studies examining critical thinking and disciplinary learning. Yin (2026), investigating Pakistani universities, found that students generally perceive AI as a collaborative partner capable of supporting academic work. At the same time, many participants expressed concern that excessive reliance on AI could diminish their critical thinking abilities. A similar perspective is advanced by Nada Hashmi (2024), who conceptualizes AI as a mentor whose recommendations should be continuously questioned and interrogated rather than accepted uncritically. These studies advocate a human-in-the-loop approach that preserves learner agency while benefiting from technological support.

Research conducted outside computing disciplines raises additional concerns regarding intellectual engagement. Qian (2025) found that AI promotes a dialogic learning process within humanities and social science education by enabling rapid interaction with ideas and texts. However, the study warns that such convenience may bypass the interpretive labor traditionally associated with deep academic inquiry. Likewise, Chan and Hu (2024) reported that AI reduces barriers to participation and increases student engagement, yet simultaneously distorts perceptions of academic competence by allowing learners to achieve outcomes that may not accurately reflect their independent abilities. These findings indicate that educational success measured through performance alone may not necessarily correspond to genuine intellectual development.

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Faculty perspectives further illustrate the complexity of AI integration within higher education. Cigdem Sengul (2024) found considerable polarization among university instructors. One group views AI as an essential component of professional preparation that reflects contemporary workplace realities, while another emphasizes risks to assessment integrity and academic authenticity. The coexistence of these contrasting viewpoints demonstrates that educational institutions continue to struggle with balancing innovation and accountability. Taken together, the reviewed studies reveal a consistent pattern. AI offers substantial benefits in terms of efficiency, accessibility, participation, and productivity, yet these advantages are accompanied by significant pedagogical, cognitive, and ethical challenges. The literature increasingly converges on the argument that successful AI integration depends not merely on adoption rates or technological capability but on the development of critical AI literacy, transparent governance structures, appropriate trust calibration, and pedagogical models that preserve human reasoning. Despite rapid progress in understanding AI's educational impact, important questions remain regarding long-term cognitive development, institutional readiness, professional skill formation, and the sustainability of AI-dependent learning practices. These unresolved issues highlight the need for further empirical and longitudinal research capable of evaluating not only what AI enables students to accomplish, but also what it means for how they learn, think, and develop expertise.

Table 1. Meta analysis of the previous studies

Author	**Year**	**Brief Topic**	**Primary Findings**	**Research Gaps**
Görkem Giray	2026	Global Software Professionals	AI adoption reduces development cycles but increases "validation overhead" by 30%.	Lacks longitudinal data on the maintainability of AI-generated legacy code.
Lidija Weis	2026	Computing Undergraduates	Students prioritize "response consistency" (3.84) over "logical accuracy" (2.90).	Does not explore the psychological drivers of this misplaced trust.
Neha Rani	2026	Engineering Education	GitHub Copilot increases code volume but induces "cognitive substitution" risks.	Minimal focus on how AI impacts non-coding engineering competencies.
Besser	2026	Professional Tech Roles	Shift from manual code construction toward high-level artifact critique.	Uncertainty regarding entry-level skill requirements for junior developers.
Lodge & Loble	2026	Australian Higher Ed	AI creates "false mastery," where students mistake output for internal understanding.	Scarcity of pedagogical frameworks to mitigate this dependency.
Hanan Alotaibi	2025	Saudi Higher Education	Performance and effort expectancy are the strongest predictors of AI adoption.	Cultural and linguistic nuances in Saudi contexts remain under-explored.

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Jiang Xiaomin	2025	Chinese University Students	Student usage projected to reach 88%; intrinsic motivation is a key adoption driver.	Overlooks the impact of institutional peer pressure on adoption rates.
Olga V. Sergeeva	2025	Institutional Readiness	Ad-hoc student usage significantly outpaces formal faculty training and ethical policy.	Lack of "best-practice" templates for mid-sized regional institutions.
Hong et al.	2025	Metacognitive Skills	High-knowledge students use AI for depth; novices use it for task avoidance.	Does not address how to bridge the "Equity Gap" for lower-baseline learners.
Qian	2025	Humanities & Social Sci.	AI facilitates a "dialogic process" but risks bypassing critical interpretive labor.	Limited empirical focus on HSS-specific hallucinations in qualitative data.
Alsham mari	2025	Technical Colleges	AI literacy and transparency are critical for maintaining teacher-student trust.	Does not provide a metric for measuring "trust erosion" over time.
Yin	2026	Pakistani Universities	Students view AI as a collaborator but fear losing critical thinking skills.	Regional focus is narrow; requires comparison with other developing economies.
Nada Hashmi	2024	Human-in-the-Loop	Argues for AI as a "mentor" whose outputs must be rigorously interrogated.	Lack of empirical validation for this model in high-enrollment classrooms.
Cigdem Sengul	2024	Faculty Perspectives	Faculty are polarized between professional prep and restrictive assessment integrity.	No clear framework for reconciling these two conflicting archetypes.
Chan & Hu	2024	Global Undergraduates	AI lowers barriers to participation but skews perceptions of academic competence.	The longitudinal impact of AI on student self-efficacy remains unknown.

2.3 Conceptual Framework

The conceptual framework for this study is based on an extended UTAUT model that positions Perceived Reliability as a critical moderating variable. The independent variables include the standard UTAUT constructs (PE, EE, SI, FC) plus AI-specific psychological factors (Trust, Privacy Concerns). The dependent variable is Adoption Readiness, measured through behavioural intention and actual usage frequency.

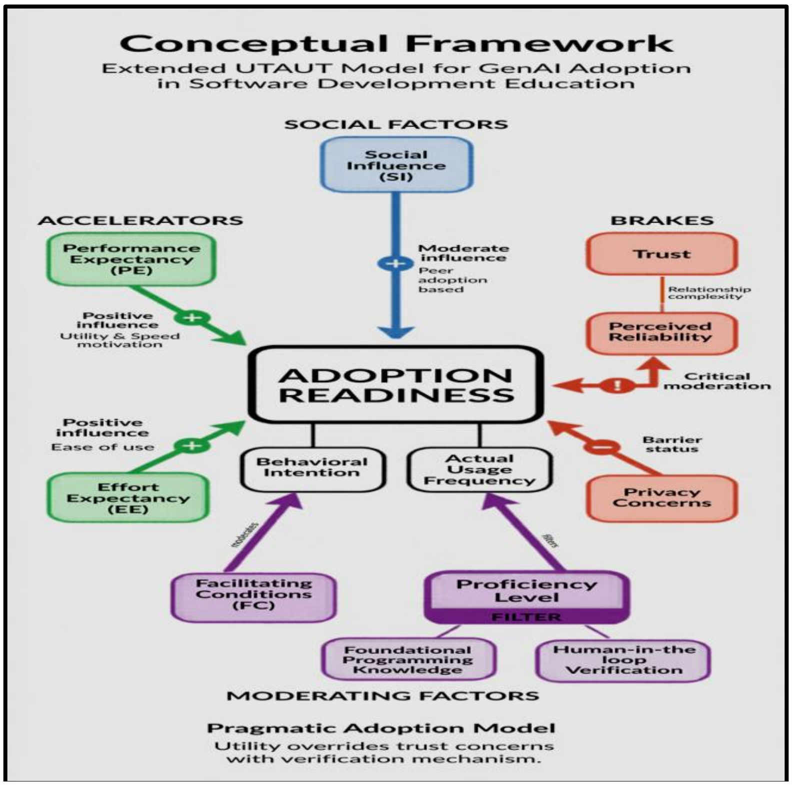

Figure 3. Mind Map - Conceptual Framework (Adoption Readiness)

In this narrative, Performance Expectancy and Effort Expectancy act as the "accelerators" of adoption, while Perceived Reliability and Privacy Concerns act as "brakes." The student's foundational programming knowledge acts as a "filter," determining their ability to effectively use AI tools without falling victim to hallucinations or vulnerabilities. The following table summarizes the key relationships analyzed.

Table 2. Conceptual Framework and Key Relationships among variables

Variable Type	Construct	Hypothesized Relationship	Supporting Context
Independent	Performance Expectancy	Positive influence on Adoption Readiness	19
Independent	Effort Expectancy	Positive influence on Adoption Readiness	12
Independent	Social Influence	Moderate influence based on peer adoption	19
Independent	Perceived Reliability	Critical moderator of long-term usage	10
Moderating	Proficiency Level	High proficiency leads to more sceptical/effective use	18
Dependent	Adoption Readiness	Drives actual academic usage behavior	11

This framework suggests that a "Pragmatic Adoption" model is at play: students are motivated by utility and speed (PE) enough to override their concerns about trust and reliability, provided they have a sufficient "human-in-the-loop" mechanism to verify the output.

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3 Research Methodology

3.1 Research Design

This study employs a quantitative, descriptive, and correlational research design. The choice of a quantitative approach allows for the measurement of the intensity of tool usage and the statistical validation of the relationships between technological constructs and student performance (Kaur, 2025). The descriptive component is used to profile the demographic and usage patterns of the student population, while the correlational component tests the hypotheses regarding the impact of AI usage on perceived skill improvement. This study looks at the patterns and measurement of usage of AI students in their studies and working. The study is cross-sectional, collecting data from a single point in time to capture the current "snapshot" of AI adoption during the 2026 academic periods. The relationship of variables is structured such that the UTAUT constructs serve as predictors of adoption readiness (the intention to use), which in turn influences the actual usage frequency. Perceived reliability is treated as a mediator that influences the transition from intention to sustained, effective usage.

3.2 Population and Sampling

The target population consists of undergraduate (BSCS/BSSE/BSIT) students from major higher education institutions in Pakistan. This includes both public sector universities (e.g., University of the Punjab, ITU) and private sector universities (e.g., FAST-NUCES, UMT, LUMS), reflecting a broad range of socioeconomic and educational backgrounds (Nada Hashmi, 2024). The originally planned sample size was 150 students, aligned with recent similar studies on technology adoption in the region (Görkem Giray, 2026). A total of 115 valid responses were received and retained for analysis, representing a response rate of 76.7%. A stratified approach was intended to represent different year levels and genders. The achieved sample predominantly comprised students from Semesters 3-4 (n=27, 23.5%) and Semesters 5-6 (n=86, 74.8%), with a minimal representation from Semesters 7-8 (n=2, 1.7%). The sampling criterion prioritized students who have had at least "beginner" experience with AI tools like ChatGPT or Copilot to ensure they could provide meaningful feedback on reliability and usability (Nikolaos Nikolaidis, 2024).

Table 3. Sampling Parameters

Year of Study	Sub-Population Detail	Sample Size Planned (n)	Sample Size Achieved (n)
Sophomore (2nd Year)	Developing core coding foundations	50	27
Junior (3rd Year)	Advanced software design focus	65	86
Senior (4th Year)	Capstone projects; industry prep	35	2
Total		150	115

Note: No Freshman (1st Year) respondents were included in the achieved sample. Semester 7-8 representation was minimal (n=2) and excluded from comparative hypothesis testing due to insufficient statistical power.

3.3 Data Collection Instruments

The primary instrument for this study is a structured, 30-item questionnaire adapted from validated technology acceptance and AI literacy scales (Stephanie A. Besser, 2026). The questionnaire is divided into six logical sections:

Table 4. Item Description of Questionnaire

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1. Demographics: Age, Gender, Semester, and Proficiency Level.
2. Awareness of GenAI: Knowledge of tool functions and institutional information (6 items).
3. Adoption Readiness: Willingness to integrate AI into academic tasks (6 items).
4. Perceived Reliability: Subjective rating of accuracy, consistency, and trust (6 items).
5. Usability and Ease of Use: User-friendliness and time-saving perceptions (6 items).
6. Challenges and Impact: Frequency of errors, ethical concerns, and perceived performance gains (12 items).

The instrument utilizes a 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree) for the behavioural items and a performance scale (1=Very Poor to 5=Excellent) for reliability metrics. Content validity was ensured through expert review by senior faculty in the CS department, and internal consistency was verified through a pilot test (n=30), yielding a Cronbach's Alpha of 0.88, indicating high reliability (Alexander Bick, 2025).

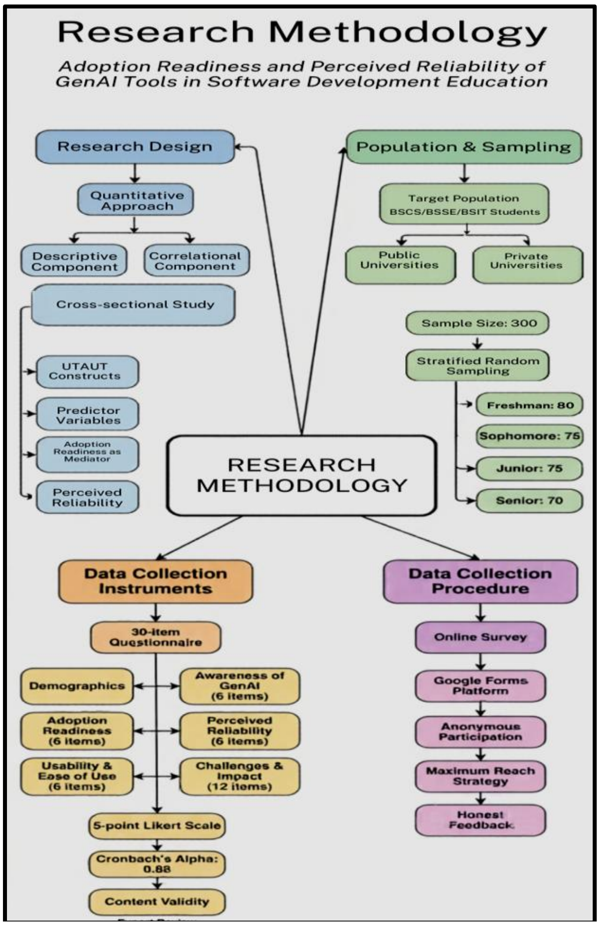

Figure 4. Research Methodology

3.4 Data Collection Procedure

The survey was administered online using Google Forms to maximize reach and ensure anonymous participation, which is critical for obtaining honest feedback on potentially sensitive topics like academic integrity (Yin, 2026). Different university students filled and submitted their responses for the forms. Institutional permission was obtained from the participating universities, and an informed consent statement was presented at the beginning of the survey, clarifying that participation was voluntary and no personal identifiers would be collected (Stephanie A. Besser, 2026).

3.5 Data Analysis Technique

The data were analysed using descriptive and inferential statistical techniques. Descriptive statistics, including means and standard deviations, were used to summarize the scores for each construct. Frequency analysis was applied to the demographic data to provide a profile of the respondents. Inferential statistics, specifically Pearson Correlation, were used to test the relationship between AI usage frequency and perceived academic performance. An independent sample t-test was employed to compare adoption readiness between genders and proficiency levels, while ANOVA was used for inter-university comparisons (Nada Hashmi, 2024).

3.6 Delimitations of the Study

The study is delimited to undergraduate computer science-related students in the Lahore region and does not include graduate researchers or students from non-technical disciplines. Furthermore, the survey focuses on general-purpose GenAI (e.g., ChatGPT) and widely used coding assistants (e.g., Copilot), excluding specialized or proprietary enterprise AI. Many platforms are now using the AI tools hence it is being used the most these days. As a cross-sectional study, it captures student sentiment at a specific point in the technology's evolution and does not track changes over a longitudinal period. Finally, the study relies on self-reported data regarding academic performance rather than actual grade point averages (GPAs), which may be subject to social desirability bias (Lidija Weis, 2026).

4. Data Analysis

4.1 Demographic Analysis

The demographic profile of the 115 respondents highlights a predominantly young student body in the 21-23 age range (73.9%), with a slight female majority (55.7%). The concentration of respondents in Semesters 5-6 (74.8%) reflects the reality that mid-program students are the most active consumers of AI tools for coursework, according to our research.

Table 5 Student Demographic Factors (n = 115)

Demographic Factor	Category	Frequency (f)	Percentage (%)
Gender	Male	51	44.3%
	Female	64	55.7%
Semester	3-4	27	23.5%
	5-6	86	74.8%
	7-8	2	1.7%
Age	18-20	24	20.9%
	21-23	85	73.9%
	24-26	6	5.2%
Proficiency	Beginner	10	8.7%
	Intermediate	86	74.8%
	Advanced	18	15.6%
AI Experience	Beginner	3	2.6%

	Intermediate	81	70.4%
	Advanced	31	27.0%

The “AI Experience” bracket is more inclined towards the “Intermediate” or “Advanced” section showing students have spent good time engaging with the new technologies in aspects of education. The high percentage of students identifying as "Intermediate" or "Advanced" in computer proficiency (90.4%) suggests that the respondents possess the necessary background to evaluate the technical accuracy of AI outputs critically (Stephanie A. Besser, 2026).

4.2 Descriptive Statistics for UTAUT Constructs

The mean scores indicate moderate-to-high awareness and usability, with challenges scoring below the neutral midpoint (2.87).

Table 6 Descriptive Statistics of Survey Section (n = 115)

Survey Section	Mean Score (1-5)	Std. Deviation
Section 1: Awareness	3.50	1.33
Section 2: Adoption Readiness	3.24	1.41
Section 3: Perceived Reliability	3.17	1.17
Section 4: Usability	3.61	1.30
Section 5: Challenges	2.87	1.42
Section 6: Perceived Impact	3.51	1.21

The highest score belongs to Usability (M=3.61), confirming that interactive ease-of-use drives initial adoption (Alexander Bick, 2025). Perceived Reliability (M=3.17) remains the lowest trust construct, reflecting the "reliability gap" that students find AI useful for routine tasks but remain sceptical for complex or high-stakes activities (Hanan Alotaibi, 2025).

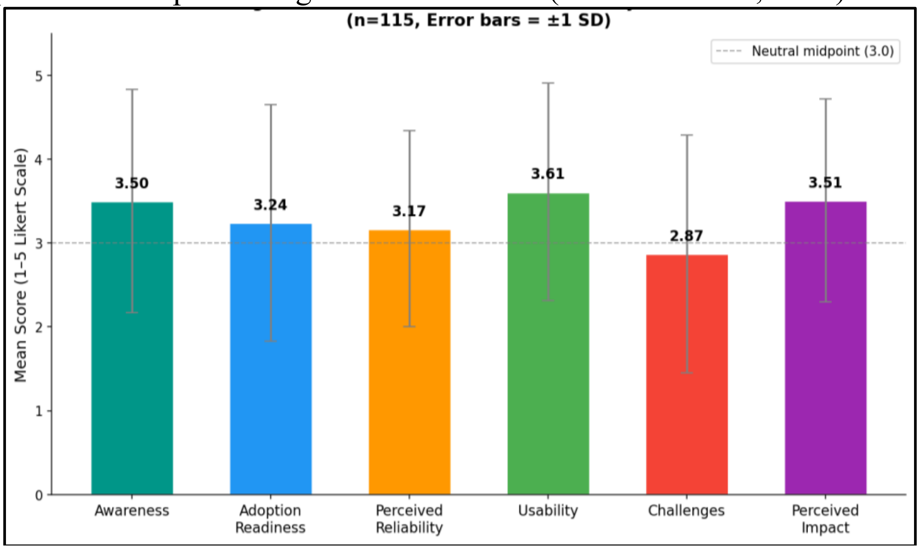

Figure 5 Mean Scores Across UTAUT Survey Sections

4.2.1 Normality Assessment

Prior to conducting parametric inferential tests (t-tests, ANOVA, Pearson correlation), the normality of construct-level score distributions were examined using the Shapiro-Wilk test alongside skewness and kurtosis indices (Figure 6).

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Table 7. Shapiro-Wilk Normality Test Results (n=115) *

Construct	Shapiro-Wilk W	p-value	Skewness	Kurtosis	Decision
Awareness	0.978	0.050	−0.295	−0.396	Normal
Adoption Readiness	0.983	0.157	0.089	−0.036	Normal
Perceived Reliability	0.978	0.058	0.043	−0.524	Normal
Usability	0.981	0.101	−0.188	0.145	Normal
Challenges	0.986	0.261	0.134	−0.121	Normal
Perceived Impact	0.972	0.016	−0.336	0.409	Approx. Normal*

Perceived Impact yields W=0.972, p=0.016 (minor deviation). However, skewness (−0.336) and kurtosis (0.409) remain well within the acceptable range of ±1.0, and with n=115 the Central Limit Theorem ensures robustness of parametric tests (Yin, 2026).

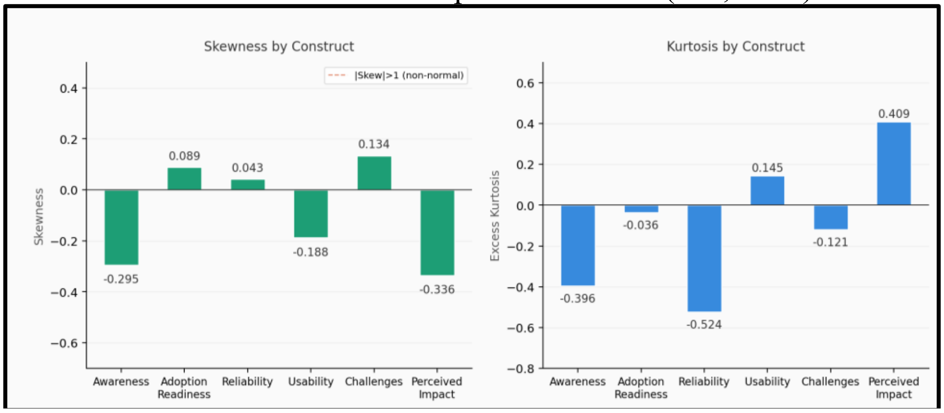

Figure 6. Normality Assessment: Skewness and Kurtosis of Construct Scores (n=115)

Five of the six constructs are non-significant on the Shapiro-Wilk test (all $p > 0.05$), confirming approximate normality. The single minor deviation from normality (Perceived Impact, p=0.016) presents negligible skewness and kurtosis, both within ±1.0, indicating that the distribution is practically normal. So, the slight deviation of Perceived Impact from Shapiro-Wilk is covered up by Skewness and Kurtosis making it still valid for the further testing. However, if the skewness and kurtosis wouldn't be able to justify it, the test plan would be reconsidered. These findings collectively justify the use of parametric inferential techniques, t-tests, ANOVA, and Pearson correlation, applied throughout this study.

4.3 Reliability and Accuracy Metrics

Item-level reliability analysis reveals that students rate the accuracy of AI-generated code as the weakest dimension (M=2.90, SD=1.45), while consistency of responses received the highest rating (M=3.84). This shows that students are not always sure about the correctness of responses in code related tasks specifically.

Table 8. Reliability and Accuracy Metrics (n = 115)

Reliability Metric	Mean Performance Score	Standard Deviation	Interpretation
Accuracy of generated code	2.90	1.45	Poor to Average

Reliability in complex logic	3.04	1.46	Average
Consistency of responses	3.84	0.43	Good
Quality of explanations	3.00	0.37	Average
Trustworthiness of solutions	3.08	1.35	Average

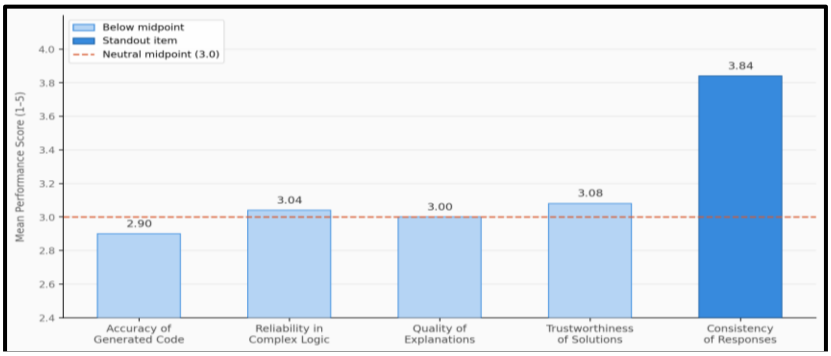

Figure 7. AI reliability metrics: mean performance scores (n=115)

Notably, the low standard deviation on consistency (0.43) and trustworthiness (0.37) suggests strong respondent agreement on these items, reflecting how students see it as reliable option but not always. These findings confirm a "Pragmatic Adoption" pattern that students leverage AI for explanation and consistency but exercise caution around logical correctness, verifying outputs themselves (Evangelista, 2024).

4.4 Inferential Statistics and Hypothesis Testing

Hypothesis H1 (Pearson Correlation): A Pearson correlation was conducted between AI usage frequency (mapped ordinally: Rarely=1, Sometimes=2, Often=3, Always=4) and mean Perceived Impact scores. The analysis yielded $r(113) = 0.105$, $p = 0.262$, indicating a weak positive but statistically non-significant relationship at $\alpha=0.05$. This overall indicates that even with extensive use of AI, it doesn't mean that it improves overall learning of students. While the direction is consistent with H1, the result suggests that usage frequency alone does not statistically predict perceived learning gains in this sample. This may reflect that the overwhelming majority of respondents (96.5%) already use AI "Often" or "Always," creating a range-restriction effect that limits the statistical power of the correlation.

Hypothesis H2 (Independent t-test): An independent sample t-test comparing Semester 3-4 students and Semester 5-6 students on Perceived Reliability mean scores yielded $t(111) = -1.506$, $p = 0.135$. While statistically non-significant at $\alpha=0.05$, the directional result is notable: contrary to the initial hypothesis, mid-program students in semesters 5-6 reported marginally higher reliability perceptions than earlier-semester students, possibly because greater exposure to AI tools normalizes its limitations. This shows that with time; the usage of AI brings more reliability and trust among students as they gain more experience in how to use it better. The small Semester 7-8 cohort (n=2) was excluded from comparative analysis due to insufficient statistical power (Yin, 2026). The effect size was small-to-medium (Cohen's $d = 0.332$), indicating that while the difference does not reach significance; it carries a practically noteworthy magnitude that warrants attention in future larger-sample replications.

Hypothesis H3 (Gender comparison): An independent sample t-test on Adoption Readiness by gender showed $t(113) = 1.271$, $p = 0.206$, a non-significant difference. Male students (M=3.32) and female students (M=3.17) reported comparably moderate adoption readiness, suggesting that gender is not a significant moderator of AI tool adoption in this sample. This indicates that gender has no significant impact overall on the adoption and usage of AI. An ANOVA

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comparing proficiency levels (Beginner, Intermediate, Advanced) on adoption readiness similarly yielded a non-significant result F (2, 112) = 0.722, p = 0.488. The associated effect size was small (Cohen's d = 0.239 for adoption readiness; d = 0.169 for reliability; d = 0.205 for perceived impact), confirming that gender accounts for negligible practical variance across all outcome constructs.

4.5 Thematic Analysis of Challenges

The analysis of Section 5 identified "Difficulty understanding AI-generated code" as the most frequently reported concern (M=3.10, SD=1.40), followed by "Worry about over-dependence" (M=2.87, SD=1.33) and "Ethical concerns in academics" (M=2.86, SD=1.44). Notably, all challenge items scored below the neutral midpoint of 3.0 except for the code comprehension item, indicating that while concerns exist, they do not dominate students' overall experience. Students may face some minor challenges like understanding how to use AI better, or if AI is degrading their personal skills but it is seen that they don't strongly feel that AI is wrong. "AI provides incorrect or misleading answers" was the lowest-rated challenge (M=2.68), suggesting students may not always recognize hallucinations when they encounter them that a finding with significant implications for AI literacy training (Kaur, 2025).

4.6 Additional Inferential Analyses

To examine the broader relational structure between all UTAUT constructs, a full Pearson correlation matrix was computed across all six survey sections (Table 9). Two statistically significant relationships emerged.

Table 9 Correlation matrix

Construct Pair	r	p-value	Significance level
Challenges → Perceived Impact	−0.289	0.002	**
Adoption Readiness → Reliability	0.216	0.020	*
Usability → Perceived Impact	0.144	0.124	ns
Reliability → Perceived Impact	0.075	0.425	ns
Awareness → Adoption Readiness	0.030	0.747	ns

First, Challenges reported a significant negative correlation with Perceived Impact, r (113) = −0.289, p = 0.002, indicating that students who encountered greater difficulties with AI tools reported meaningfully lower perceived learning gains. From t-test results we can confirm that, it takes time to learn how to use AI to yield better results, showing that in the beginning, the learning benefit may be lower but with time and proper use, it can prove to be very helpful. This is the strongest and most practically significant relationship in the dataset. Second, Adoption Readiness was positively correlated with Perceived Reliability, r(113) = 0.216, p = 0.020, suggesting that students who trusted AI outputs more were also more willing to integrate these tools into their academic work, consistent with the UTAUT mediating role of reliability proposed in the research framework. The more they 'believe' in the results the AI yields, the more they rely on AI tools for their academic works.

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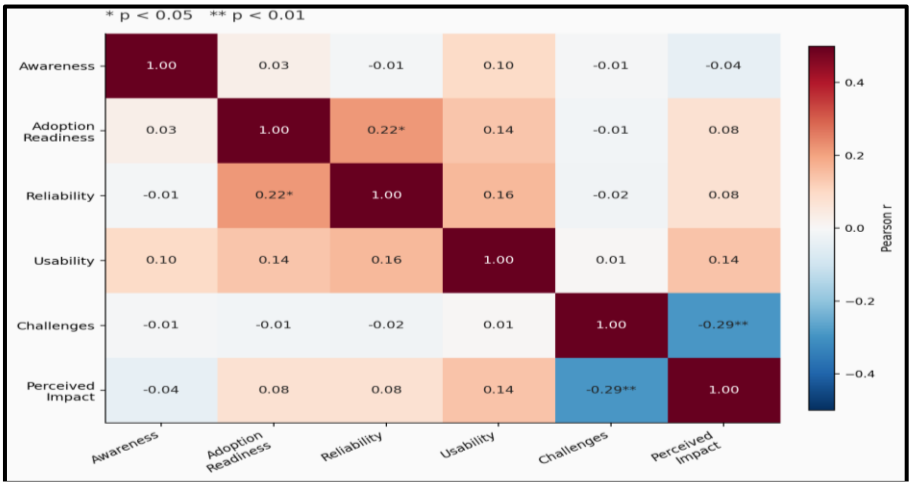

Figure 8 Pearson Correlation Matrix

5. Implications of the Study

The Unified Theory of Acceptance and Use of Technology (UTAUT) must fundamentally evolve in light of the theoretical environment of the AI era. According to research, the concept of "Effort Expectancy" has shifted from tool operation to the cognitive labor of output verification, with perceived reliability emerging as the main mediator between initial acceptance and persistent use. Social Cognitive Theory's "triadic reciprocity" argues that when users engage with GenAI as a "human-social partner," pupils modify their tactics in response to AI feedback, occasionally putting consistency ahead of accuracy. A correlation between adoption readiness and reliability ($r = 0.216$) supports this "consistency-over-accuracy" tolerance pattern, which emphasizes that trust is an ongoing reinforcer rather than a static precondition. This calls for new theoretical constructs like "emotional dependency" to account for the anthropomorphic nature of these tools. The transition from "syntax mastery" to adversarial verification and process-based schooling is necessary from a practical and political standpoint as AI integration advances. Teachers must address "output opacity" by forcing pupils to trace and explain AI-generated code because high usage frequency does not associated with substantial learning gains ($p = 0.262$). To avoid a new digital gap, institutional policies must give up "laggardness" in favour of established frameworks that include required faculty development, equal access to premium resources, and transparent tiered disclosure. In the end, effective integration ensures that students maintain ultimate control over the engineering process rather than becoming intellectually reliant on the tools they use by changing Key Performance Indicators (KPIs) from straightforward adoption metrics to the calibre of the "human-in-the-loop" interaction.

6. Conclusion

The integration of Generative AI into software development education is characterized by a "Reliability-Utility Paradox": tools like ChatGPT and GitHub Copilot are embraced for their immense potential to boost productivity and reduce cycle time, yet they are simultaneously mistrusted for their tendency to produce logical errors and security vulnerabilities. The findings highlight a significant positive correlation between AI usage and perceived learning efficiency, but they also raise a red flag regarding cognitive dependency. If students utilize these tools as "shortcuts" without a solid theoretical foundation, they risk losing the critical thinking skills that are the hallmark of a skilled engineer. AI may provide ease in yielding good results but with the risk that it provokes dependency and over reliance.

The quantitative evidence presented in this study, particularly the significant negative relationship between perceived challenges and learning impact ($r = -0.289$, $p = 0.002$) and the confirmation that Adoption Readiness is significantly linked to Perceived Reliability ($r = 0.216$, $p = 0.020$) that collectively paint a picture of a student population that is navigating an unprecedented technological transition without adequate institutional support. Students are more open to the use of AI by themselves, than the most of educational institutions, creating a gap in education methodologies. The near-universal usage rates observed in this sample (96.5% using AI "Often" or "Always") represent an irreversible behavioral shift that curriculum design and academic policy have not yet caught up with. This study contributes a data-driven foundation for institutions in Pakistan and the broader South Asian higher education context to design that response with evidence rather than assumption. It is also important to acknowledge the study's limitations as part of a transparent conclusion. The cross-sectional design captures a single moment in a rapidly evolving technological landscape. The reliance on self-reported performance data introduces the possibility of social biasness, and the concentration of the sample in Semesters 3-4, 5-6 limits the generalizability of findings to early-stage or near-graduation students, indicating the limitations of data collection. These limitations do not invalidate the findings but initialize them as a starting point, the first systematic quantitative snapshot of AI adoption readiness among computing students in the Pakistani higher education context, upon which more rigorous longitudinal and multi-institutional research should be built.

7. Recommendations

A multifaceted strategy is needed to guarantee the responsible and successful integration of generative AI in software development education. First, as a credit-bearing subject that specifically addresses prompt engineering, AI debugging, and security vulnerability identification, software engineering departments should formally incorporate AI-Assisted Development into the curriculum. A "human-in-the-loop" methodology that uses AI as a learning scaffold rather than a replacement should be used to support this program. Under this methodology, students must turn in reflection logs with their AI-assisted assignments, outlining the precise actions they took to confirm and adjust the AI's recommendations. Lastly, educational institutions ought to give professional preparedness and learning sustainability top priority. In order to take advantage of the current skill distribution in the classroom and guarantee that students who are technically advanced receive help for the ethical use of these tools, peer learning communities should be developed. Universities should carry out longitudinal research, monitoring student cohorts over time to determine whether early reliance on generative AI impacts independent problem-solving and professional performance as they enter the workforce, in order to assess the long-term efficacy of these interventions.

This study establishes a baseline for understanding how undergraduate computing students in Pakistan perceive and adopt Generative AI tools in their academic work. However, several important questions remain unanswered and constitute a productive agenda for future research. The most immediate priority is a longitudinal follow-up. The cross-sectional design of this study cannot answer whether the "Pragmatic Adoption" pattern observed here represents a stable equilibrium or a transitional phase. The study should include periodic responses over a duration for better understanding the effect of usage with time. Second, the scope of this study was deliberately limited to general-purpose AI (ChatGPT) and code-specific assistants (GitHub Copilot). The emergence of deeply integrated AI-native development environment such as agentic coding tools that autonomously plan, write, test, and debug entire software systems, fundamentally changes the nature of the human-AI interaction being studied. More advanced methodologies and tools would be needed for that. Future research should examine how these more autonomous tools affect students' sense of agency, ownership of their code, and development of debugging intuition, outcomes that are not captured by UTAUT-based frameworks designed for assistive rather than autonomous technologies.

Finally, the Pakistan-specific context of this study, while a contribution to an underrepresented body of literature, is also a limitation. On global context, this study may follow different approach. Comparative cross-national studies examining how cultural attitudes toward academic integrity, institutional trust in technology, and socioeconomic access to premium AI tools moderate the adoption patterns documented here would substantially advance the theoretical generalizability of UTAUT-based AI adoption models in Global South higher education contexts.

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Appendix

Research Questionnaire

Adoption Readiness and Perceived Reliability of Generative AI Tools in Software Development Education

Introduction
Respected Participant,
We are students of BSCS conducting a research study on the adoption readiness and perceived reliability of generative AI tools in software development education. The purpose of this study is to understand students’ perceptions, usage behaviour, and trust in AI tools such as ChatGPT and other coding assistants. Your responses are highly valuable and will contribute to academic research. All information collected will remain strictly confidential and used only for research purposes. No personal identity will be disclosed.
Consent Statement,

- Participation is voluntary.
- Responses are confidential and anonymous.
- You may withdraw at any time.
- The information is used for academic purposes only.

☐ I have read the above information and agree to participate.
Demographic Information
Please select (✓) the option that best describes you. (Multiple Choice)

Question	Options (Multiple Choice)

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1. Age	18–20 ☐ 21–23 ☐ 24–26 ☐ Above 26
2. Gender	☐ Male ☐ Female ☐ Prefer not to say
3. Semester	☐ 1–2 ☐ 3–4 ☐ 5–6 ☐ 7–8
4. Area of Study	☐ Computer Science ☐ Software Engineering ☐IT ☐ Other
5. Computer Proficiency Level	☐Beginner ☐ Intermediate ☐ Advanced
6. Experience with AI Tools	☐ None ☐ Beginner ☐ Moderate ☐ Extensive
7. Frequency of Using AI Tools	☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐ Always

Section 1: Awareness of Generative AI Tools

Please read each statement carefully and tick (✓) the option that best represents your opinion.

Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Response Scale		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
No.	Statement / Item	1	2	3	4	5
1	I am aware of generative AI tools used in software development.	☐	☐	☐	☐	☐
2	I know how AI tools assist in coding tasks.	☐	☐	☐	☐	☐
3	I understand the basic functioning of generative AI tools.	☐	☐	☐	☐	☐
4	My institution provides information about AI tools.	☐	☐	☐	☐	☐
5	I stay updated about new AI technologies in programming.	☐	☐	☐	☐	☐
6	I have learned about AI tools through academic courses.	☐	☐	☐	☐	☐

Section 2: Adoption Readiness

Please read each statement carefully and tick (✓) the option that best represents your opinion.

Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Response Scale →		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
No.	Statement / Item	1	2	3	4	5
1	I am willing to use AI tools in my programming tasks.	☐	☐	☐	☐	☐
2	I feel comfortable integrating AI tools into my learning.	☐	☐	☐	☐	☐

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3	I am open to replacing traditional methods with AI tools.	☐	☐	☐	☐	☐
4	I believe AI tools improve my coding efficiency.	☐	☐	☐	☐	☐
5	I am ready to rely on AI tools for assignments.	☐	☐	☐	☐	☐
6	I would recommend AI tools to my classmates.	☐	☐	☐	☐	☐

Section 3: Perceived Reliability of AI Tools

Please rate each item based on your experience with AI tools.

Scale: 1 = Very Poor | 2 = Poor | 3 = Average | 4 = Good | 5 = Excellent

Response Scale →		Very Poor	Poor	Average	Good	Excellent
No.	Statement / Item	1	2	3	4	5
1	Accuracy of AI-generated code.	☐	☐	☐	☐	☐
2	Reliability of AI tools in solving programming problems.	☐	☐	☐	☐	☐
3	Consistency of AI responses.	☐	☐	☐	☐	☐
4	Trustworthiness of AI-generated solutions.	☐	☐	☐	☐	☐
5	Quality of explanations provided by AI tools.	☐	☐	☐	☐	☐
6	Dependability of AI tools during complex tasks.	☐	☐	☐	☐	☐

Section 4: Usability and Ease of Use

Please read each statement carefully and tick (✓) the option that best represents your opinion.

Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Response Scale →		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
No.	Statement / Item	1	2	3	4	5
1	AI tools are easy to use.	☐	☐	☐	☐	☐
2	AI interfaces are user-friendly.	☐	☐	☐	☐	☐
3	I can quickly learn how to use AI tools.	☐	☐	☐	☐	☐
4	AI tools save time in coding tasks.	☐	☐	☐	☐	☐
5	AI tools simplify complex programming concepts.	☐	☐	☐	☐	☐

6	AI tools improve my productivity.	☐	☐	☐	☐	☐

Section 5: Challenges and Concerns

Please read each statement carefully and tick (✓) the option that best represents your opinion.

Scale: 1 = Never | 2 = Rarely | 3 = Sometimes | 4 = Often | 5 = Always

Response Scale →		Never	Rarely	Sometimes	Often	Always
No.	Statement / Item	1	2	3	4	5
1	I face difficulty understanding AI-generated code.	☐	☐	☐	☐	☐
2	AI tools provide incorrect or misleading answers.	☐	☐	☐	☐	☐
3	I worry about over-dependence on AI tools.	☐	☐	☐	☐	☐
4	I feel AI reduces my problem-solving skills.	☐	☐	☐	☐	☐
5	I face ethical concerns using AI tools in academics.	☐	☐	☐	☐	☐
6	I encounter technical issues while using AI tools.	☐	☐	☐	☐	☐

Section 6: Impact on Learning and Performance

Scale: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Response Scale		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
No.	Statement / Item	1	2	3	4	5
1	AI tools enhance my learning experience.	☐	☐	☐	☐	☐
2	AI tools improve my programming skills.	☐	☐	☐	☐	☐
3	AI tools help me complete assignments faster.	☐	☐	☐	☐	☐
4	AI tools increase my confidence in coding.	☐	☐	☐	☐	☐
5	AI tools help me understand concepts better.	☐	☐	☐	☐	☐
6	AI tools positively impact my academic performance.	☐	☐	☐	☐	☐