

FROM CODING TO AI-ASSISTED DEVELOPMENT: EXAMINING DEVELOPERS' ACCEPTANCE OF GENERATIVE AI THROUGH AN EXTENDED TAM

Umair Jamil Ahmad^{*1}, Anees Muhammad², Dr. Asif Ali Jamali³

^{*1}Senior Lecturer, Department of computer science, SZABIST University Hyderabad

²Lecturer, University of Sufism and Modern Sciences, Bhitshah

³Assistant Professor, Department of Software Engineering University of Sindh Jamshoro

^{*1}umair.queshi@hyd.szabist.edu.pk/ umairjqueshi@gmail.com, ²dr.aneesjamali@gmail.com,
³asif.jamali@usindh.edu.pk

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Corresponding Author: *

Umair Jamil Ahmad

Abstract

The swift adoption of AI in software development is reshaping traditional coding methodologies and presenting novel opportunities for AI-driven development. But besides the technical qualities of the technology, developers need to consider perceptions of the usefulness, ease of use, trust and risk. In this study, an extended Technology Acceptance Model (TAM) was used to explore the acceptance of generative AI-based development by developers. The model included perceived usefulness, perceived ease of use, perceived risk, and perceived trust as antecedents of the attitude, and behavioral intention and use of the AI-assisted development followed. The quantitative cross-sectional design was used, and a purposive sampling technique was used to collect data from software developers, software engineers, programmers and IT professionals of Karachi and Hyderabad, Sindh, Pakistan, a total of 229 respondents were sampled. Partial Least Squares Structural Equation Modeling – SmartPLS was used to analyze the data. The results showed that perceived usefulness, perceived ease of use, and trust had a positive effect on developers' attitudes, while perceived risk had a significant negative effect. The attitude was found to have a strong influence on the behavioral intention, which, in turn, predicted the use of AI-assisted development. The mediation effect and sequential mediation of attitude and behavioral intention was also confirmed, further explaining the mediation results obtained. The results of the mediation were further confirmed by the significant mediation and sequential mediation of attitude and behavioral intention. The study reveals that developer-centric strategies for sustainable software development are required, as developers' perceptions of both facilitating and perceived barriers to the adoption of generative AI affects their adoption.

Introduction

Generative AI is disrupting the traditional software development model and moving the programming tasks from manual coding to AI support. By enhancing code generation, debugging, documentation, testing, and problem solving, Generative AI tools are opening up fresh possibilities for developers to boost software development efficiency and productivity. For software engineering, the use of generative AI brings a significant amount of complexity as there are technological, organizational, and human-related challenges that come with the benefits, according to Russo (2024). Similarly, Park (2025) shows that developers' ongoing usage of AI coding assistants relies on their perceptions and experiences with large language model-based technologies. Likewise, Anditama and Hidayanto (2024) discuss several factors that influence the acceptance of software developers towards the use of Artificial Intelligence Assistants and argue that examining the adoption of AI tools from a user acceptance perspective is crucial, as it goes beyond a mere technological view. The integration of generative AI in software development is also growing more common and is still evolving, as noted by Gurgul et al. (2026), but the patterns of adoption and usage are still different among developers and development contexts. Another piece of evidence from Ansari (2026) shows how AI can contribute to software project productivity, highlighting the growing need to understand developers' readiness to integrate AI into their software development processes. As a result, systematic research is needed to gain insight into the factors that affect developers' receptivity of generative AI when moving from traditional coding to AI-assisted coding.

However, the adoption of generative AI by software developers isn't just about its technical capabilities; developers need to see the technology itself as useful, usable, trustworthy, and safe enough to utilize in their work. The TAM is an appropriate theoretical underpinning for the study of technology-related perceptions, as perceived usefulness and perceived ease of use

can account for users' attitudes and their resulting behavioral intentions regarding emerging technologies. Conventional acceptance factors can be extrapolated to cover the unique nature of AI-based programming technologies as Pan et al. (2024) show by their expanded TAM. Similarly, Ali et al. (2025) demonstrate that building trust and learning motivation can enhance an extended TAM to account for the use of AI coding assistants in programming learning. Additionally, Kim et al. (2025) confirm that both perceived usefulness and perceived enjoyment are factors influencing the acceptance of AI coding assistants, revealing that there are functional and experiential assessments. The empirical findings from Shao and Ishengoma (2026) on the adoption of generative AI in software development underscore the importance of studying the factors that influence the adoption of AI within real software development environments. In addition to technological benefits, Anditama and Hidayanto (2024) note that several other factors influence developers' decisions on using AI assistants. Therefore, supplementing TAM with constructs like trust and perceived risk can offer a broader understanding of developers' attitudes and intentions towards generative AI-assisted development.

While there has been significant research into the use of AI coding assistants and more recently, generative AI more generally, there is a key research gap surrounding the degree to which developers are putting generative AI at the heart of software development, and the extent to which they are aware of the benefits and risks this can bring. Research that looked at continuance use by industry developers, educational adoption by programming learners, and other factors determining AI-assisted software development have been conducted separately from each other, and needs to be combined and represented in a single acceptance framework, which takes both positive and negative perceptions of generative AI into account. Park (2025) offers rich insights on the continuance use of software by industry developers, and Russo (2024) discusses the

intricacies of the software industry's use of generative AI. Additionally, Noor (2025) presents a list of opportunities and challenges that arise when it comes to software development teams that rely on generative AI, highlighting the potential gains and potential pitfalls of using AI in the software development industry that can affect developers' acceptance of the technology. Elias and Jafari (2026) build on this by exploring how AI tools for coding affect agile software development methods, revealing the broader implications of AI use in modern software development. Shao & Ishengoma (2026) empirically investigate the adoption of generative AI in software development, and Gurgul et al. (2026) give a more general view of the current landscape of generative AI in software development at a developer level. Inspired by the aforementioned advancements, the present study thus calls for an extended TAM by adding perceived usefulness, perceived ease of use, trust, and perceived risk to explain attitude, behavioral intention, and the use of generative AI-assisted software development among software developers as a whole.

Aim

This study will explore the acceptance of generative AI for AI-assisted software development by the developers using an extended Technology Acceptance Model (TAM). It also aims to elucidate the mechanism of influence that perceived usefulness, perceived ease of use, trust and perceived risk have on AI adoption via attitude and behavioral intention..

Objectives

1. To examine the effect of perceived usefulness on developers' attitude toward generative AI-assisted development.
2. To assess the effects of perceived ease of use, trust, and perceived risk on developers' attitude toward generative AI-assisted development.
3. To determine the effect of attitude on developers' behavioral intention to use generative AI for software development.

4. To examine the effect of behavioral intention on developers' actual AI-assisted development use.
5. To investigate the mediating effects of attitude and behavioral intention in the relationships between the extended TAM factors and AI-assisted development use.

Literature review

As AI coding assistants become more common in the software development industry, the literature shows their ability to influence traditional software development tasks and technology choices. The growing body of literature on the use of generative AI in software development highlights how the technology is transforming the ways developers undertake typical software development tasks and make related decisions. The adoption of Generative AI is crucial in the current landscape of software engineering and poses significant challenges, particularly in code generation, debugging, documentation, testing, and problem solving. Park (2025) found that developers' continuance use of AI coding assistants is associated with their perceptions and experiences with large language model-based coding technologies, highlighting the importance of examining acceptance beyond initial adoption. Developers' acceptance of AI assistants goes beyond the availability of AI tools, as Anditama and Hidayanto (2024) found it to be influenced by several factors. In addition, Shao and Ishengoma (2026) offer empirical evidence that technology- and user-related factors affect the adoption of generative AI in software development. Similarly, Gurgul et al. (2026) have stated the increased relevance of generative AI to software development and noted that the patterns in which developers are using generative AI and how they view the technologies vary. While generative AI can offer several advantages to development teams, it also presents challenges, including reliability, collaboration, and responsible use, as Noor (2025) pointed out. In addition, Elias and Jafari (2026) link the use of AI in coding with current agile software development approaches, suggesting that the

impact of AI reaches beyond coding to the software development process. Overall, this literature provides a solid foundation for understanding that the adoption of generative AI by developers is a multi-faceted issue that necessitates a thorough examination of developers' perceptions underlying their readiness to employ generative AI in software development tasks.

Another body of literature illustrates how technology acceptance model serves as a good framework for understanding the adoption of AI-based technologies, but specific factors that affect what makes a technology more or less acceptable must be added to this model, as generative AI has unique properties. Perceived usefulness and perceived ease of use will always be essential factors, as developers are more inclined to adopt AI coding assistants when they believe they can see the benefit in doing so and that it is not too difficult to use (Arzu et al. 2025; Shah et al. 2017). By extending the TAM, Pan et al. (2024) illustrate that the model can be applied successfully in explaining students' willingness to utilize AI coding assistants, highlighting the importance of TAM in an AI-supported programming environment. Ali et al. (2025) take the next step by adding trust and learning motivation to TAM and highlight their importance for the adoption of AI coding assistants. Additionally, Kim et al. (2025) demonstrate that the factors of perceived usefulness and perceived enjoyment are linked to AI coding assistant adoption, indicating how both utilitarian and experiential perceptions can impact technology adoption. In a similar way, Mao et al (2024) use a hybrid TAM framework for training and adoption of generative design assistants, also showing the applicability of TAM to new generative AI environments. Wang and Yu (2026) further reinforce the above-mentioned TAM-based explanation of generative AI acceptance by analyzing factors that impact the acceptance of generative AI teaching assistants. Zhou et al. (2025) also demonstrate the applicability of an expanded TAM to behavioral intention toward generative AI in another creative domain. The findings of these studies

collectively point to a need for conventional TAM constructs as good explanatory starting points, but also to the need for using additional context-specific factors like trust and perceived risk for explaining developers' acceptance of generative AI supported software development.

Theoretical framework

Theoretically, the present study builds upon the Technology Acceptance Model (TAM) that offers a succinct construct for understanding the influence of users' perceptions of a technology on their attitudes and behavioral intentions to use it. In the proposed context of AI coding tools, Perceived Usefulness (PU) indicates the developers' beliefs that the generative AI can enhance their coding and software development abilities, while Perceived Ease of Use (PEOU) describes developers' perceptions of the ease of use and learning of AI coding tools. The core TAM constructs are expected to affect the developers' Attitude toward Generative AI, which will then affect their Behavioral Intention to Use, and finally, AI-Assisted Development Use. But modern AI tools are probabilistic and generative, with factors that are not adequately represented by traditional TAM. Thus, the framework adds Positive Acceptance Factor (Trust in Generative AI) and Perceived Risk (as a possible barrier to acceptance) to extend the TAM. Ali et al. (2025) show that trust is a crucial factor in AI coding assistant extended TAM, and Anditama and Hidayanto (2024) confirm the significance of several factors in the software developers' adoption of AI assistants. The adoption of generative AI in software engineering is complex, and there is a need for a context-sensitive theoretical framework, as Russo (2024) highlights. Park (2025) offers evidence on developers' ongoing use of AI coding assistants, and Shao and Ishengoma (2026) further emphasize the need to study the use of generative AI in software development empirically.

Hypotheses

Direct relationships with Attitude

- **H1:** Perceived Usefulness has a significant positive effect on developers'

attitude toward generative AI-assisted development.

- **H2:** Perceived Ease of Use has a significant positive effect on developers' attitude toward generative AI-assisted development.
- **H3:** Trust in Generative AI has a significant positive effect on developers' attitude toward generative AI-assisted development.
- **H4:** Perceived Risk has a significant negative effect on developers' attitude toward generative AI-assisted development.
- **H5:** Attitude toward generative AI-assisted development has a significant positive effect on developers' behavioral intention to use generative AI.
- **H6:** Behavioral intention to use generative AI has a significant positive effect on AI-assisted development use among developers.

Mediation hypotheses

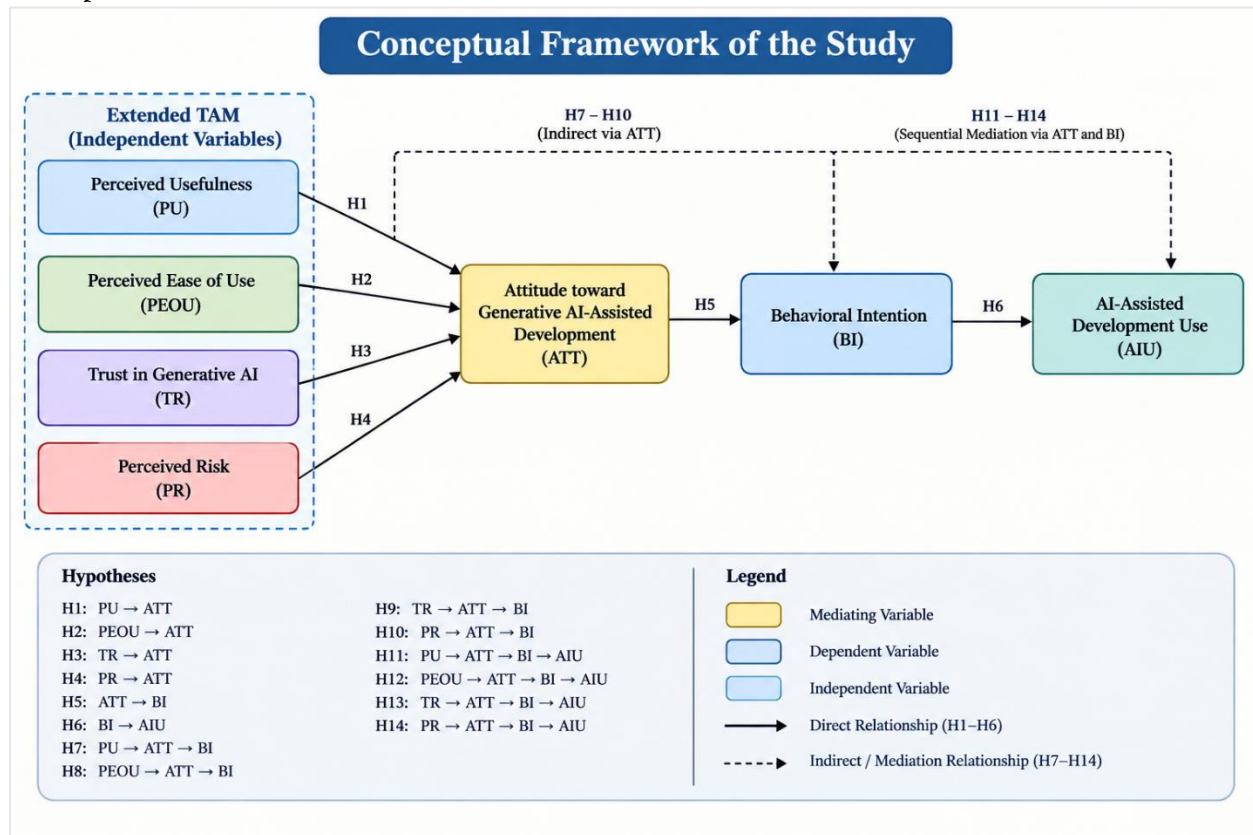
- **H7:** Attitude toward generative AI-assisted development mediates the relationship between perceived usefulness and behavioral intention to use generative AI.
- **H8:** Attitude toward generative AI-assisted development mediates the relationship between perceived ease of

use and behavioral intention to use generative AI.

- **H9:** Attitude toward generative AI-assisted development mediates the relationship between trust in generative AI and behavioral intention to use generative AI.
- **H10:** Attitude toward generative AI-assisted development mediates the relationship between perceived risk and behavioral intention to use generative AI.

Sequential mediation

- **H11:** Attitude toward generative AI-assisted development and behavioral intention sequentially mediate the relationship between perceived usefulness and AI-assisted development use.
- **H12:** Attitude toward generative AI-assisted development and behavioral intention sequentially mediate the relationship between perceived ease of use and AI-assisted development use.
- **H13:** Attitude toward generative AI-assisted development and behavioral intention sequentially mediate the relationship between trust in generative AI and AI-assisted development use.
- **H14:** Attitude toward generative AI-assisted development and behavioral intention sequentially mediate the relationship between perceived risk and AI-assisted development use.



Methodology

A quantitative and cross sectional research method was used to study the acceptance of generative AI for AI assisted software development from an extended Technology Acceptance Model (TAM). Purposive sampling was employed to gather data from the respondents which included 229 software developers, software engineers, programmers and IT professionals from Karachi and Hyderabad, Sindh, Pakistan. The respondents were those who have had experience using generative AI tools for coding, debugging, code generation, testing, documentation, or software development in other related areas. The data was collected by using a structured questionnaire with a 5-point Likert scale and analyzed by implementing a Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis using the SmartPLS software. PLS-SEM was deemed suitable for the current study, since it was an extension of an

existing theoretical model and multiple relationships between latent variables included mediation relationships (Hair et al., 2017). All the measures were examined for indicator reliability, internal consistency reliability, convergent validity, discriminant validity, path coefficients, bootstrapping, coefficient of determination, effect sizes, predictive relevance, and mediation analysis for the assessment of the structural model. The use of this methodological approach allowed for the empirical exploration of the relationships between the extended TAM dimensions, attitude, behavioral intention and the use of AI in development.

Measure

The constructs were measured using previously validated scales adapted to the context of generative AI for software development. Because of the conceptual foundation of the Technology Acceptance Model developed by Davis (1989),

both Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) were measured using the 6 items developed by Davis (1989). The items that measure Attitude toward Generative AI-Assisted Development (ATT) were adapted from Ali et al. (2025), which used an extended TAM to measure AI-coding assistant adoption, items that measure Behavioral Intention (BI) were adapted from Ali et al. (2025), items that measure AI-Assisted Development Use (AIU) were adapted from Ali et al. (2025). Trust in Generative AI (TR) was assessed using 4 items that were adapted from the trust-related measures used by Ali et al. (2025). Perceived Risk (PR) was assessed by 4 items adapted from existing works of AI-adoption and perceived-risk literature, and customized to the context of generative AI assisted software development. A 5-point Likert scale from 1 = strongly disagree to 5 = strongly agree was used for all items. Minor wording modifications were made to ensure that the items specifically reflected developers' use of generative AI in

software development. The questionnaire had 29 measurement items, with the exception of the demographic and screening items.

Demographic Profile

The demographic profile was analyzed to gain insights into the makeup of the 229 respondents who took part in the study about the developers' acceptance of generative AI in software development. The profile took into account relevant aspects related to the adoption of technology, such as gender, age, educational qualification, professional experience, job role, geographical location and experience of using generative AI tools. That is because the developers' experiences with software development and AI technologies might have an impact on their perceptions of usefulness, ease of use, trust, perceived risk, attitude, behavioral intention, and actual use of AI in software development.

Table 1. Demographic Profile of Respondents

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	155	67.69
	Female	74	32.31
	Total	229	100.00
Age	20–25 years	72	31.44
	26–30 years	82	35.81
	31–35 years	45	19.65
	36–40 years	20	8.73
	Above 40 years	10	4.37
	Total	229	100.00
Educational Qualification	Bachelor's degree	113	49.34
	Master's degree	93	40.61
	MPhil/MS	18	7.86
	PhD	5	2.18
	Total	229	100.00
Professional Experience	Less than 2 years	54	23.58
	2–5 years	86	37.55
	6–10 years	57	24.89
	11–15 years	22	9.61
	More than 15 years	10	4.37
	Total	229	100.00
Job Role	Software Developer	91	39.74

	Software Engineer	63	27.51
	Programmer	38	16.59
	Full-Stack Developer	21	9.17
	Other IT/Technical Role	16	6.99
	Total	229	100.00
Location	Karachi	151	65.94
	Hyderabad	78	34.06
	Total	229	100.00
Experience with Generative AI Tools	Less than 6 months	45	19.65
	6 months–1 year	68	29.69
	1–2 years	73	31.88
	More than 2 years	43	18.78
	Total	229	100.00

Demographic results showed that it was mainly male that responded to the survey, 67.69%, versus the females 32.31%. As far as the age is concerned, the maximum number of respondents were in the age group of 26-30 years (35.81%) followed by 20-25 years (31.44%), which indicated that the sample was mainly composed of relatively younger Software Professionals. In terms of education, almost half of the respondents had a bachelor's degree (49.34%), while 40.61% had a master's degree. Professional experience was mainly focused on 2–5 years (37.55%) and 6–10 years (24.89%). The greatest number of professional groups were software developers (39.74%) and software engineers (27.51%). From a geographic point of view, 65.94% respondents lived in Karachi while 34.06% lived in Hyderabad. Importantly, 60.35% of the respondents had used generative AI tools at least

for one year, which suggests that they had enough exposure to generative AI-assisted development to give meaningful feedback on its usefulness, ease of use, trust, perceived risk, behavioral intention, and actual use.

Descriptive Statistics and Reliability of Constructs

The descriptive and reliability results show that the respondents overall reported moderately high perceptions of the usefulness and ease of use of generative AI in software development with mean scores of 3.91 and 3.86, respectively. The mean values for the other variables, trust, attitude, behavioral intention, and AI-assisted development, were higher than the midpoint of the five-point scale, while the perceived risk variable showed a relatively low mean of 3.21.

Table 2. Descriptive Statistics and Reliability of Constructs

Construct	Items	Mean	Standard Deviation	Cronbach's Alpha (α)	rho_A	Composite Reliability (CR)
Perceived Usefulness (PU)	6	3.91	0.71	0.914	0.917	0.933
Perceived Ease of Use (PEOU)	6	3.86	0.69	0.902	0.905	0.925
Trust in Generative AI (TR)	4	3.74	0.76	0.876	0.881	0.916
Perceived Risk (PR)	4	3.21	0.83	0.861	0.867	0.906
Attitude (ATT)	3	3.88	0.73	0.884	0.887	0.928
Behavioral Intention	3	3.79	0.78	0.872	0.876	0.920

(BI)						
AI-Assisted Development Use (AIU)	3	3.68	0.81	0.859	0.864	0.914

The reliability coefficients also suggest the internal consistency of the constructs is satisfactory. The Cronbach's alpha values were between 0.859 and 0.914, and the rho_A values were between 0.864 and 0.917. Likewise, composite reliability values ranged from 0.906-0.933. All reliability coefficients were above the acceptable level of 0.70, indicating that the constructs were internally consistent and appropriate for further measurement and examination of their structural model.

Convergent and Discriminant Validity

The measurement results show good convergent validity and discriminant validity of all constructs. The AVE values ranged from 0.674 to 0.811, which is higher than the recommended level of 0.50, showing that the variance of the indicators explained by each construct was greater than 50%. The square root of AVE was also higher than the correlations of each construct with the other constructs, which also met the Fornell-Larcker criterion.

Table 3. Convergent and Discriminant Validity

Construct	AVE	PU	PEOU	TR	PR	ATT	BI	AIU
PU	0.700	0.837						
PEOU	0.674	0.612	0.821					
TR	0.733	0.548	0.526	0.856				
PR	0.706	-0.318	-0.291	-0.365	0.840			
ATT	0.811	0.672	0.638	0.601	-0.347	0.900		
BI	0.792	0.641	0.606	0.574	-0.329	0.734	0.890	
AIU	0.780	0.578	0.551	0.526	-0.301	0.671	0.758	0.883

Note. Diagonal values in bold represent the square root of AVE (Fornell-Larcker criterion). Off-diagonal values represent inter-construct correlations.

Moreover, all HTMT values were below the conservative value of 0.85, and the highest value was for the correlation between Behavioral Intention and AI-Assisted Development Use (0.837). These results all suggest that the

constructs were empirically distinct, and that the measurement model had acceptable convergent and discriminant validity, which would facilitate the subsequent evaluation of the structural model.

Structural Model and Hypothesis Testing

Table 4. Structural Model and Hypothesis Testing

Hypothesis	Structural Path	β	STDEV	TValue	P-Value	Decision
H1	PU $\rightarrow$ ATT	0.286	0.067	4.269	0.000	Supported
H2	PEOU $\rightarrow$ ATT	0.214	0.071	3.014	0.003	Supported
H3	TR $\rightarrow$ ATT	0.263	0.065	4.046	0.000	Supported
H4	PR $\rightarrow$ ATT	-0.157	0.061	2.574	0.010	Supported
H5	ATT $\rightarrow$ BI	0.734	0.039	18.821	0.000	Supported
H6	BI $\rightarrow$ AIU	0.758	0.042	18.048	0.000	Supported
H7	PU $\rightarrow$ ATT $\rightarrow$ BI	0.210	0.052	4.038	0.000	Supported
H8	PEOU $\rightarrow$ ATT $\rightarrow$ BI	0.157	0.054	2.907	0.004	Supported
H9	TR $\rightarrow$ ATT $\rightarrow$ BI	0.193	0.050	3.860	0.000	Supported
H10	PR $\rightarrow$ ATT $\rightarrow$ BI	-0.115	0.047	2.447	0.014	Supported
H11	PU $\rightarrow$ ATT $\rightarrow$ BI $\rightarrow$ AIU	0.159	0.040	3.975	0.000	Supported
H12	PEOU $\rightarrow$ ATT $\rightarrow$ BI $\rightarrow$ AIU	0.119	0.041	2.902	0.004	Supported
H13	TR $\rightarrow$ ATT $\rightarrow$ BI $\rightarrow$ AIU	0.146	0.039	3.744	0.000	Supported
H14	PR $\rightarrow$ ATT $\rightarrow$ BI $\rightarrow$ AIU	-0.087	0.036	2.417	0.016	Supported

Note. β = standardized path coefficient; STDEV = standard deviation; T = t-statistic; p = significance probability. A hypothesis was considered supported when $p < 0.05$.

Attitude have shown significant positive influence on Behavioral Intention that has then shown strong positive influence on AI-Assisted Development Use. The results of mediation showed that the mediation effect of Attitude was significant for the relationship between four extended TAM dimensions and Behavioral Intention as well. The mediation results using the sequential mediation model were also consistent, which showed that Perceived Usefulness and Perceived Ease of Use mediated the effects of Perceived Risk, Trust, and Perceived Usefulness on the AI-Assisted Development Use. In summary, all fourteen hypotheses were supported, and the study revealed the explanatory

The structural model results indicate that all hypothesized relationships were statistically significant. Perceived Usefulness, Perceived Ease of Use, and Trust positively influenced developers' Attitude toward generative AI-assisted development, while Perceived Risk exerted a significant negative influence.

value of the extended TAM when it comes to developers' acceptance and use of generative AI for software development.

Coefficient of Determination and Effect Size

The results indicate that the structural model demonstrated meaningful explanatory power for the endogenous constructs. The predictors explained 54.2% of the variance in Attitude, while Attitude explained 53.9% of the variance in Behavioral Intention. Behavioral Intention, in turn, explained 57.5% of the variance in AI-Assisted Development Use, indicating substantial explanatory capability of the model.

Table 5. Coefficient of Determination and Effect Size

Endogenous Construct	R ²	R ² Adjusted	Predictor	f ²	Effect Size
Attitude (ATT)	0.542	0.532	PU $\rightarrow$ ATT	0.118	Small

			PEOU → ATT	0.071	Small
			TR → ATT	0.103	Small
			PR → ATT	0.041	Small
Behavioral Intention (BI)	0.539	0.537	ATT → BI	1.170	Large
AI-Assisted Development Use (AIU)	0.575	0.573	BI → AIU	1.375	Large

Note. R^2 = coefficient of determination; f^2 = effect size. Following commonly used PLS-SEM guidelines, f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

The f^2 assessment showed that Perceived Usefulness, Perceived Ease of Use, Trust, and Perceived Risk each contributed a small effect to Attitude, whereas Attitude demonstrated a large effect on Behavioral Intention and Behavioral Intention demonstrated a large effect on AI-Assisted Development Use. Overall, the findings suggest that the extended TAM provided considerable explanatory power in predicting developers' acceptance and actual use of generative AI-assisted development.

Discussion

The results showed that perceived usefulness, perceived ease of use and trust had significant and positive effects on developers' attitudes towards generative AI-assisted development, while perceived risk had a significant negative effect. This was followed by a positive correlation between attitude and behavioral intention which significantly predicted the use of AI-assisted development, and the mediation results validated the mediation effect of attitude in the path between behavioral intention and its effects. This research results confirm the predictive relevance of the TAM that was first introduced by Davis (1989) and which states that perceived usefulness and perceived ease of use are central factors in understanding the acceptance of technology. The positive impact of trust is aligned with Ali et al. (2025), which found that trust-related perceptions are crucial in the adoption of AI-coding assistants, and the negative effect of perceived risk mirrors the general challenges of AI-coding assistant adoption revealed by Russo (2024). Likewise, Pan et al. (2024) showed that an extended TAM could explain users' willingness to use AI coding assistants and Park (2025) pointed out the role of acceptance-related perceptions in

developers' continued use of AI coding assistants. In summary, the results support the extended TAM as a suitable model to explain developers' adaptation to the use of AI tools for software development.

Recommendations

To give developers opportunities to explore the uses of generative AI through practical, hands-on training, coding workshops and supervised implementation, software organizations must offer structured opportunities for developers to experiment with these tools. There is a need for organizations to focus on trustworthy and safe AI tools and to have policies and procedures in place to verify code, protect and secure data, safeguard intellectual property, and ensure responsible use of AI. The developers should be encouraged to use generative AI as an augmentation mechanism rather than a replacement for professional judgment. There are also opportunities for organizations to create peer-learning communities where developers can exchange valuable insights on effective prompting, debugging techniques, validation approaches, and successful use of AI to aid in their workflows. AI tools should be regularly evaluated to pinpoint any usability issues, security risks, and performance limitations. Such efforts can boost developer trust, mitigate risk, and foster continued adoption of generative AI in software development.

Limitations and Future Directions

This study's limitations were related to its cross sectional design, purposive sampling, relatively small sample size of 229 respondents, and the focus on developers in Karachi and Hyderabad, Sindh, Pakistan. Therefore, the results might not

be generalizable to other developers in other provinces in Pakistan or in other international software programming environments or organizations with varying levels of AI maturity. The study was also self-reported, and may have been influenced by common-method or social-desirability bias. Longitudinal designs could be used in future studies to explore how the developers' acceptance shifts over time as they become more familiar with the use of generative AI. Larger probability-based samples in various regions and countries could also be used for analysis, and developers could be compared based on their experience, organizational type, programming specialization, or the level of AI usage. Additional constructs that may be added to future models include perceived enjoyment, AI self-efficacy, output quality, concerns about privacy, organizational support, perceived compatibility, and technological readiness.

Implications

The study offers theoretical, methodological, and practical implications for the understanding of the adoption of generative AI in software engineering. In theory the addition of trust and perceived risk in the model of TAM makes it more complete as it explains both enabling and inhibiting perceptions. From a methodological perspective, the study provides an example of how PLS-SEM can be used to assess the direct and sequential mediation relationships of multiple relationships in an AI-adoption model. In practice, the results indicate that software companies should not only take into account the technical skills required to use the generative AI tools, but also the developers' perception of usefulness, usability, trust, and risk. The psychological aspects of the attitude-behaviour relationship also signal that to achieve effective AI transformation, the technology must be available and suitable, alongside developers' psychological acceptance. The framework thus offers a foundation for organizations to create developer-focused AI adoption strategies.

Conclusion

The study found that the acceptance of generative AI assisted development by the developers can be meaningfully and partially explained by an extended Technology Acceptance Model (TAM) that includes four additional factors: perceived usefulness, perceived ease of use, perceived trust and perceived risk. The results revealed that positive attitudes were more likely to emerge when developers felt generative AI to be helpful, easy to use and reliable, and negative attitudes were more likely to emerge when developers felt that generative AI posed a threat. These perceptions then were converted into increased behavioral intentions, and their significance in the technology-acceptance process was reflected in the attitude of the developers. The sequential mediation results also confirmed that attitude and behavioral intention were a critical pathway between the extended TAM dimensions and actual use of AI-assisted development.

The study further found that the adoption of the shift from traditional coding to AI-assisted coding goes beyond the mere presence and complexity of the generative AI tools. Instead, the ability to successfully adopt these technologies hinges on the value, usability, trustworthiness, and risks developers believe in. The study brings these together into one all-encompassing acceptance model for developer-centric adoption of generative AI. The results offer a basis for the software industry and tech leaders and researchers to build responsible and sustainable practices for AI-driven software development that leverages the capabilities of generative AI while preserving the human element—judgement, verification, accountability.

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