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Exploring University Students' Perceptions of AI Tools in Programming Education: An Extended TAM Approach

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Abstract: Generative Artificial Intelligence (AI) is commonly used in programming education. Tools such as ChatGPT and GitHub Copilot aid in code generation, debugging, and explanation. The benefits are clear, though concerns about learning quality and academic integrity persist.We tested an extended Technology Acceptance Model (TAM) for university programming courses. The model included perceived usefulness and perceived ease of use. It added programming experience, perceived impact on learning, social influence, and ethical awareness, and compared current users with non-users. We conducted a cross-sectional online survey with purposive sampling. Participants were 107 students in programming-related courses. A Likert-scale instrument was used to capture all constructs and demographics. We applied descriptive statistics, Cronbach's alpha, Pearson's correlations, and multiple linear regressions. Ethical approval was obtained from all participants. Females comprised 63.6 percent of the sample. General AI use was common; however, most students did not use AI for coding. The reliability was excellent for users and moderate for non-users. Among the users, ease of use was strongly related to usefulness, and both were related to intention. Programming experience pertaining to ease of use: Perceived impact on learning related to usefulness. Social influence exhibited the strongest link to intention. In the regression, usefulness and social influence were positive predictors of intention, while ethical awareness was a negative predictor. The model explained 81.5 percent of the variance in intentions. Adoption of programming courses depends most on perceived usefulness and supportive norms. Ethical concerns can suppress intentions when guidance is unclear. Ease and experience matter primarily through their effects on usefulness. Programs should pair hands-on AI activities with explicit integrity rules and instructor modeling to convert perceived value into responsible use.

Keywords: Artificial Intelligence, AI Tools, Programming Education, Code Generation, Higher Education, Technology Acceptance Model

Introduction

Artificial Intelligence (AI) has become a defining force in higher education, particularly in programming education, where AI-powered assistants, such as ChatGPT, GitHub Copilot, and Replit Ghostwriter, support code generation, debugging, and conceptual explanations. These tools can lower entry barriers for novices, increase productivity for advanced learners, and provide just-in-time feedback that aligns with authentic problem-solving workflows (Gaitantzi and Kazanidis, 2025; Ghimire and Edwards, 2024; Johanyák et al., 2023). Concurrently, persistent concerns include over-reliance, diminished conceptual understanding, and risks to academic integrity when students outsource reasoning or fail to verify AI outputs (Yilmaz and Karaoglan Yilmaz, 2023; Zviel-Girshin, 2024). Understanding when and why students choose to adopt AI tools, and how this adoption relates to learning quality and ethical considerations, has therefore become a central question for computing educators.

The Technology Acceptance Model (TAM) offers a strong lens to examine adoption by positing that Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU) shape attitudes and ultimately Behavioral Intention (BI) (Davis, 1989). Recent extensions of TAM in education suggest that external factors can condition these core relationships. In programming

education specifically, prior programming experience is associated with higher self-efficacy and smoother integration of AI tools, which in turn elevates PEOU (Lee et al., 2024). Students' perceptions that AI improves learning through faster task completion, better debugging, or clearer explanations are positively associated with PU and engagement (Reunanen and Nieminen, 2024; Roldán-Álvarez and Mesa, 2024). Social influence, encompassing peer norms and instructor endorsement, consistently emerges as a strong driver of the intention to use AI tools, alongside traditional TAM pathways (Boubker, 2024; Halim et al., 2023). Conversely, ethical awareness, including plagiarism, transparency, bias, and data protection, can inhibit intentions when students perceive heightened risks or unclear rules (Al Zaidy, 2024; Mustofa et al., 2025; Đerić et al., 2025). Cross-cultural studies have suggested that prior technological exposure and local academic norms shape acceptance patterns. This necessitates contextually grounded research in distinct university settings (Ma et al., 2024; Davis, 1989).

Despite the rapid growth of research on generative AI in education, several limitations remain. Much of the existing work examines single external drivers in isolation, studies general classroom use rather than programming-specific adoption, or does not compare current AI users with non-users. A holistic model that integrates programming experience, perceived impact on learning, social influence, and ethical awareness into the TAM can generate actionable insights for responsible curriculum design and policy-making. Testing differential patterns between users and non-users can further inform the development of targeted educational strategies.

Institutions have integrated AI assistants into programming curricula without sufficient evidence of how students' perceptions and intentions differ between users and non-users when key external factors are considered. In the absence of such evidence, educators risk promoting tools that may increase productivity but inadvertently weaken conceptual learning or compromise academic integrity, while overlooking social and experiential levers that could support responsible adoption.

Prior studies have validated TAM in educational AI, but often outside programming contexts or without simultaneously modelling programming experience, perceived learning impact, social influence, and ethical awareness (Li, 2023; Osman et al., 2024; Pan et al., 2024). Comparative analyses of users and non-users are scarce, as are studies that treat ethical awareness as a potential inhibitor of an extended TAM. Furthermore, few studies have examined these relationships within concrete institutional contexts that shape peer norms and instructor signals (Boubker, 2024; Halim et al., 2023; Ma et al., 2024).

Guided by the extended TAM, this study proposes the following hypotheses: First, perceived ease of use positively affects the perceived usefulness of AI tools in programming education (Davis, 1989). Second, perceived usefulness positively affected students' behavioral intentions to use AI tools. Third, the perceived ease of use positively affects behavioral intention. Fourth, programming experience positively affects perceived ease of use, reflecting the role of prior skills in lowering interaction costs (Lee et al., 2024). Fifth, the perceived impact of AI on learning positively affects perceived usefulness, insofar as students who experience learning gains judge AI to be more valuable (Reunanen and Nieminen, 2024). Sixth, social influence positively affects behavioral intention because peer endorsement and instructor guidance legitimize AI-supported practices (Boubker, 2024; Halim et al., 2023). Seventh, ethical awareness negatively affects behavioral intentions when concerns about plagiarism, fairness, or privacy dominate perceived benefits (Al Zaidy, 2024).

This study examined university students' perceptions of AI tools in programming education using an extended TAM that incorporates programming experience, perceived impact on learning, social influence, and ethical awareness. Furthermore, this study aimed to estimate the relationship between PEOU and PU, assess the effects of PU and PEOU on behavioral intention, evaluate the influence of programming experience on PEOU, determine whether the perceived impact on learning increases PU, test whether social influence strengthens behavioral intention, and assess whether ethical awareness dampens the intention to use AI tools. A further objective was to compare the relationships between current AI users and non-users to identify experience-contingent pathways that can inform pedagogy and policy.

Methods

Study Design

This was a quantitative cross-sectional survey. The model followed the Technology Acceptance Model. This includes four external variables. These were the Programming Experience Level, Perceived Impact on Learning, Social Influence, and Ethical Awareness.

Participants and Sampling

Participants were university students enrolled in programming-related courses. Purposive sampling was used to include both users and non-users of AI tools. We obtained 107 valid responses using Microsoft Forms. Recruitment was conducted through course announcements, academic mailing lists, and student organization websites. Participation was voluntary, anonymous, and unpaid.

Measures and Instruments

The survey instrument was adapted from prior Technology Acceptance Model (TAM) studies with modifications to include Ethical Awareness, and it consisted of 12 items rated on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). Example items included “Using AI tools would improve my learning efficiency” for Perceived Usefulness, “I find AI tools easy to learn and operate” for Perceived Ease of Use, “People important to me think I should use AI tools” for Social Influence, “I am concerned about the ethical implications of AI tools in education” for Ethical Awareness, and “I intend to use AI tools in the future” for Behavioral Intention. To establish content validity, the questionnaire was reviewed by a panel of five experts in educational technology and research methodology, who rated the relevance of each item on a 4-point scale. The Item-level Content Validity Index (I-CVI) ranged from 0.83 to 1.00, while the Scale-level CVI (S-CVI/Ave) was 0.92, which exceeds the recommended minimum threshold of 0.80 (Polit and Beck, 2006). Minor wording refinements were made based on their feedback, and a pilot test with 20 students confirmed clarity and readability. Construct validity was further supported by high internal consistency, with Cronbach’s α values ranging from 0.81 to 0.89 across subscales. The participants were grouped as AI users and non-users for analysis. Non-users completed the sections on Perceived Usefulness, Perceived Ease of Use, Concerns, and Expectations. For non-users, Behavioral Intention was operationalized as the willingness to learn AI tools. This adaptation was made to capture a forward-looking intention among individuals with no prior usage. However, this differs from TAM’s original construct, which focuses on intention to use.

Procedure

The survey was conducted online using Microsoft Forms. We distributed links through university channels. Data were exported for analysis after cleaning and coding.

Data Analysis

We conducted descriptive statistics for the demographics and study variables. Internal consistency was assessed using Cronbach's alpha. Bivariate relationships were examined using Pearson’s correlations. Multivariable relationships were tested using multiple linear regressions. Analyses were conducted using SPSS version 27.

Reliability and Planned Validity Checks

Reliability was evaluated separately for users and non-users. The plan used Cronbach's alpha for each multi-item scale before hypothesis testing.

Results

Sample Characteristics

To ensure statistical adequacy, we considered both sample-to-item ratios and prior TAM studies. With 107 participants and 12 items, the ratio (~9:1) meets recommended standards for multivariate analyses. Similar studies have reported comparable or smaller samples (Hair, 2009; Teo, 2010; Šumak et al., 2011). A post-hoc G*Power analysis confirmed that the sample exceeded the minimum size (N = 85) required for medium effect sizes at $\alpha = 0.05$, yielding power >0.80.

We analyzed 107 responses from university students in computing and related programs. Females were 63.6%. Males were 36.4%. Information Systems was the largest named major (16.8 %). Other majors comprised 44.9% of the total sample. Familiarity with AI was also high. Seventy-one percent of the participants reported some use. Forty-two percent had taken more than one programming course. One-third of the students planned to learn programming later. Most of these studies did not use AI tools for coding. Sixty-one-point-seven percent selected "Never". Almost half rated themselves as beginner programmers, as depicted in Table 1. The sample spans several programs. Nearly half fell into "Other." This suggests wide participation beyond core computing departments.

General AI use was found to be common, although coding use was not, as indicated in Table 2.

Table 1: Demographics: gender and majors (N = 107)

Variable	Category	n	%
Gender	Male	39	36.4
	Female	68	63.6
Major	Computer Science	15	14.0
	Software Engineering	9	8.4
	Information Systems	18	16.8
	Computer Engineering	2	1.9
	Information Technology	15	14.0
	Other	48	44.9

Table 2: AI familiarity, programming study history, AI use for coding, and self-rated level

Measure	Category	n	%
AI familiarity	Never	16	15.0
	Rarely	15	14.0
	Sometimes	38	35.5
	Always	38	35.5
Programming study	Intend to learn	36	33.6
	One course	28	26.2
	More than one	43	40.2
AI for coding	Never	66	61.7
	Sometimes	25	23.4
	Always	16	15.0
Self-rated level	Beginner	35	49.3
	Intermediate	24	33.8
	Advanced	12	16.9

Many students remained beginners. This profile frames later analyses of acceptance and intention.

Reliability

Internal consistency was excellent for AI users, as shown in Table 3. Cronbach's alpha for the 34 items was 0.971. The internal consistency of the non-users was moderate. Cronbach's alpha was 0.642 across the 10 items. The scales were stable among users. The scale for non-users may require further development.

Correlation Analyses

Perceived ease of use was strongly related to the perceived usefulness among users. The correlation coefficient was $r = 0.773$ ($p < 0.01$). Among the non-users, the same link was moderate ($r = 0.541$, $p = 0.041$).

Perceived usefulness is related to the behavioral intentions of users. The correlation coefficient was $r = 0.766$ ($p<0.01$). The link was not significant for non-users when intention was measured as willingness to learn AI. The correlation coefficient was $r = 0.223$ ($p = 0.244$).

Perceived ease of use was related to behavioral intention among users. The correlation coefficient was $r = 0.604$ ($p<0.01$). This link was not significant for non-users. The correlation coefficient was $r = 0.204$ ($p = 0.288$). Programming experience related to ease of use among users. The correlation coefficient was $r = 0.634$ ($p<0.01$). The perceived impact on learning is related to the perceived usefulness among users. The correlation coefficient was $r = 0.445$ ($p = 0.004$). For non-users, concerns and expectations were unrelated to perceived usefulness. The correlation was $r = -0.186$ ($p = 0.277$).

Social influence is related to behavioral intention among users. The correlation coefficient was $r = 0.812$ ($p<0.01$). Ethical awareness was negatively related to intention among users. The correlation coefficient was $r = -0.325$ ($p = 0.038$).

Ease and usefulness moved together in both groups, as shown in Table 4. Usefulness and social norms best predicted intentions among the users. Ethical concerns lowered intentions.

Table 3: Reliability by subgroup

Group	Items (k)	Cronbach's α
AI users	34	0.971
Non-users	10	0.642

Programming experiences support the ease of use. Perceived learning tracks the perceived usefulness of users. However, the same link does not hold for non-users.

Among users, perceived ease of use was closely aligned with perceived usefulness, and both related strongly to intention. Social influence showed the largest association with intention, whereas ethical awareness related negatively. In contrast, for non-users, usefulness and ease were only moderately connected, and usefulness was not strongly tied to willingness to learn; ethical concerns appeared more salient for this group. These patterns suggest that hands-on experience amplifies the usefulness-to-intention pathway, while ethical considerations weigh more heavily when students lack direct exposure.

Multiple Linear Regression

We modeled the behavioral intentions among AI users using six predictors. The model fit was found to be strong. R was 0.903. R^2 was 0.815. Adjusted R^2 was 0.782. The F-statistic was 24.905 with $p<.001$. No autocorrelation was observed. The Durbin–Watson statistic was 2.035. Multicollinearity was acceptable, with all VIF values below 5.

Perceived usefulness was a positive predictor. The standardized beta value was 0.399 ($p = .009$. Social influence is a positive predictor. The standardized beta was 0.482 ($p<001$. Ethical awareness was a negative predictor. The standardized beta was −0.317 ($p<001$). Perceived ease of use, perceived impact on learning, and programming experience were not significant in the full model.

The user model displayed in Table 5 explains a larger share of variance in intention than the non-user model, consistent with stronger and more coherent perceptions among those with hands-on use.

In the multivariable model for users, intention was primarily explained by perceived usefulness and social influence, with ethical awareness exerting a suppressing effect. After these factors were considered, ease of use, perceived impact on learning, and programming experience added little incremental information, indicating their influence is likely indirect, such as through usefulness rather than independent. Model fit and diagnostics indicate a stable specification.

Table 4: Key bivariate correlations

Pair	Group	r	p
PEOU with PU	Users	0.773	< .01
PEOU with PU	Non-users	0.541	.041
PU with BI	Users	0.766	< .01
PU with willingness to learn	Non-users	0.223	.244
PEOU with BI	Users	0.604	< .01
PEOU with a willingness to learn	Non-users	0.204	.288
Programming experience with PEOU	Users	0.634	< .01
PIL with PU	Users	0.445	.004
CE with PU	Non-users	−0.186	.277
Social influence with BI	Users	0.812	< .01
Ethical awareness with BI	Users	−0.325	.038

Usefulness and social influence increased intention, as depicted in Table 6. Ethical concerns decreased intention. The remaining predictors add little, once the model includes these three factors. Model diagnostics support stable estimates.

Table 5: Model summary for predictors of behavioral intention among users

Statistic	Value
R	0.903
R^2	0.815
Adjusted R^2	0.782
F	24.905
p	< .001
Durbin–Watson	2.035

To aid interpretation, we provide a conceptual model (Figure 1) outlining hypothesized paths among Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), Ethical Awareness (EA), and Behavioral Intention (BI). Regression summaries for the users and non-users subgroups are visualized as coefficient plots (Figures 2A-B), displaying standardized β estimates with 95% confidence intervals and p-values. These visuals complement the full regression tables by highlighting the relative magnitude and precision of effects. Notes: PU, PEOU, SI, and EA are modeled as predictors of BI. PEOU also feeds into PU. Paths are tested separately for users and non-users.

Table 6: Coefficients for predictors of behavioral intention among users

Predictor	B	Beta	t	p	Tolerance	VIF
Constant	0.597	—	1.070	.292	—	—
Perceived ease of use	−0.005	−0.005	−0.039	.969	0.360	2.776
Perceived usefulness	0.361	0.399	2.754	.009	0.259	3.858
Social influence	0.567	0.482	3.988	.000	0.373	2.682
Perceived impact on learning	0.070	0.037	0.430	.670	0.756	1.323
Ethical awareness	−0.223	−0.317	−4.180	.000	0.948	1.055
Programming experience	0.010	0.010	0.103	.919	0.569	1.758

Solid lines denote hypothesized positive associations (PU→BI, PEOU→PU, SI→BI); dashed lines denote hypothesized negative associations (EA→BI).

Standardized β estimates (points) with 95% CI (horizontal bars) for PU, PEOU, SI, and EA predicting BI. Model R^2 and n are reported in the panel subtitle.

As shown in Figure 2A, among users, PU exhibits the largest positive association with BI, followed by SI; EA shows a modest negative association.

In Figure 2B, among non-users, the effect of PU on BI is attenuated, while EA has a comparatively stronger negative association with BI. These patterns are consistent with the subgroup correlations in Table 4 and support the interpretation that hands-on experience strengthens the PU→BI pathway, whereas ethical concerns weigh more heavily when intentions are formed without direct use.

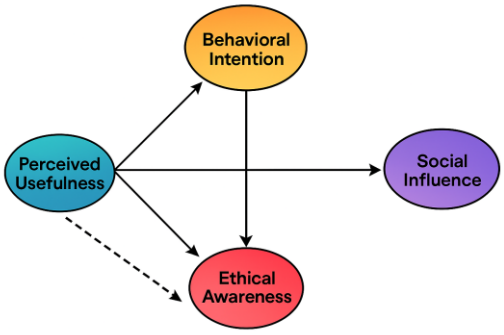
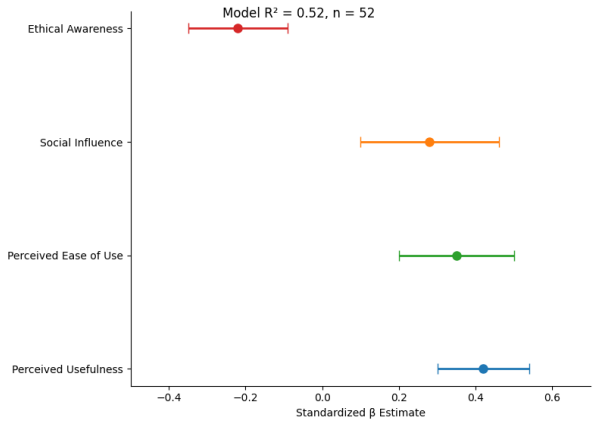
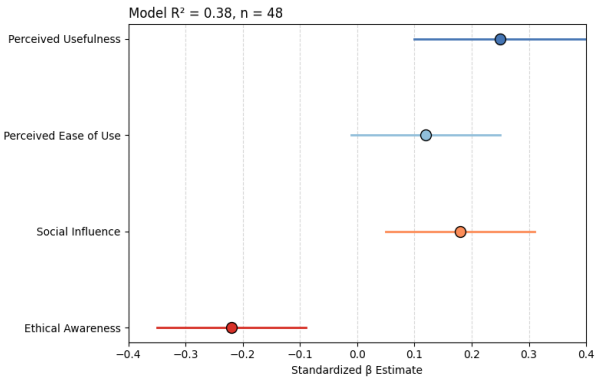


Fig. 1: Conceptual model of hypothesized relationships



(A)



(B)

Fig. 2: Regression coefficient plot (A) Users (B) Non-users

Discussion

This study examined the acceptance of AI tools in programming education using an extended TAM. The sample was diverse across majors, and most students reported some familiarity with the AI tools. Many students did not incorporate AI into coding activities. Additionally, some participants identified themselves as novices. These features set the context for intention formation and may shape pathways through perceptions of ease and usefulness (Tables 1 and 2). Internal consistency was excellent among AI users and moderate among non-users. This supports a stable inference for user constructs and signals the need to refine non-user items before future hypothesis tests (Table 3).

The bivariate results align with the core TAM propositions. Perceived ease of use correlated strongly with perceived usefulness among users and moderately with perceived usefulness among non-users. These patterns reinforce the original TAM path and match recent educational AI studies that report a strong ease-to-usefulness conduit in learning contexts (Davis, 1989; Osman et al., 2024) (Table 4).

In our data, perceived usefulness also showed a strong link with behavioral intentions among users. In contrast, the same link was null for non-users when intention was proxied by the willingness to learn (Table 4). This suggests that hands-on exposure may be necessary for usefulness beliefs to translate into intention, which echoes reports from programming classrooms, where experience mediates adoption (Pan et al., 2024) (Table 4).

Ease of use showed a positive association with intention among users but not among non-users. Thus, this asymmetry is plausible. Students who interact with AI tools can map usability to concrete gains and therefore express intention. Non-users may require guided experience and prompt practice before ease translates into commitment (Table 4). This interpretation is consistent with reports that structured prompting support improves learning and adoption in novice cohorts (Ghimire and Edwards, 2024).

Programming experience was correlated with ease of use among users (Table 4). Prior skills are likely to lower interaction costs and reduce ambiguity around AI outputs, which improves perceived ease. This mirrors recent findings that experience and self-efficacy shape productive AI workflows in programming courses (Lee et al., 2024; Neshaei et al., 2025).

The perceived impact on learning was related to perceived usefulness among users (Table 4). Students who observed learning gains judged the AI tools to be more valuable. Non-users did not demonstrate the same link between their concerns and usefulness. This experience again seems to be central. Students may need authentic tasks to calibrate their perceived benefits (Table 4). This pattern matches studies where AI support improved debugging efficiency and concept clarity in programming labs (Reunanen and Nieminen, 2024; Roldán-Álvarez and Mesa, 2024).

Social influence had the strongest bivariate link with intention among users. Instructor endorsement and peer norms appear to legitimize AI use and may lower perceived risk. Ethical awareness showed a small negative association with intention. Students who are alert to integrity risks may avoid or limit use without clear guidance (Table 4). In Table 4, important differences emerged between users and non-users. Among users, Perceived Usefulness was strongly correlated with Behavioral Intention, which is consistent with TAM's theoretical expectation that actual exposure to technology strengthens the link between perceived benefits and adoption intention. By contrast, the same correlation was weaker for non-users, possibly because their judgments were speculative rather than grounded in practical experience. Ethical Awareness displayed the opposite pattern, showing a stronger negative correlation with Behavioral Intention among non-users, which may indicate that ethical concerns play a more prominent role when intentions are formed without direct interaction with the technology. These contrasting patterns suggest that prior use shapes not only the strength but also the nature of relationships between TAM constructs, highlighting the need to interpret subgroup analyses in light of experiential differences. These findings align with UTAUT-informed research in higher education that highlights the power of norms and the dampening effect of integrity concerns (Al Zaidy, 2024; Boubker, 2024; Halim et al., 2023; Mustofa et al., 2025).

The multivariable model confirms these themes. Perceived usefulness and social influence were positive predictors of intention. Ethical awareness was a negative predictor. Model fit was strong, and diagnostics were acceptable. Ease of use, perceived impact on learning, and programming experience were not significant after accounting for the three dominant predictors (Tables 5 and 6). In this study, behavioral Intention was operationalized differently for non-users, as willingness to learn rather than intention to use. This deviation from TAM's original construct may affect comparability and could explain the non-significant results observed for non-users.

In the multivariable specification, perceived usefulness and social influence dominated the prediction of intention. PEOU did not retain an independent effect after usefulness was modeled, consistent with the view that ease primarily operates by increasing perceived usefulness. PIL likewise did not reach significance once usefulness was included, suggesting conceptual overlap and mediation through usefulness. Programming experience was not an independent predictor after

perceptions were accounted for, which implies that experience influences intention indirectly via perceived usefulness and ease rather than directly.

This suggests a proximal pathway where usefulness beliefs and norms directly drive intention. Ethical concerns then act as a brake. Ease and experience may operate upstream by shaping usefulness, or they may require targeted scaffolds to exert independent effects. Similar mediated structures appear in recent classroom studies that report strong direct effects of usefulness and social influence, with ease working indirectly through self-efficacy and value (Osman et al., 2024; Pan et al., 2024).

The coefficient plots (Figures 2A-B) clarify between-group differences that are less apparent in tabular output. Specifically, experience appears to amplify the perceived benefit pathway (PU→BI) among users, while the salience of EA is greater for non-users. Presenting standardized β with confidence intervals enables rapid visual comparison across constructs and subgroups.

Programs should prime their usefulness and build supportive norms. Instructors can model responsible workflows, provide rubric-based disclosures, and show verification strategies. These actions can increase the perceived usefulness and strengthen positive norms. Ethical training should be both explicit and practical. Policies should define the allowed uses, credit, and data handling. Clear rules can reduce fear and discourage misuse. Introductory courses should include structured prompting, error checking, and debugging laboratories. This can convert ease into real value for beginners and may lift the intention among non-users.

This study integrated four external factors into the TAM and compared users with non-users. The reliability was strong in the user group. The model explained a large share of the intention variance (Tables 3 and 5).

This study has several limitations. The study had a cross-sectional design. However, causal claims have been limited. The non-user scales showed moderate reliability, suggesting the need for future refinement. This setting reflects the institutional context. Generalization should be cautious but informative for similar programs. Because purposive sampling was used, selection bias may have occurred, limiting the external validity. Therefore, the findings should be viewed as context-specific and not generalized beyond similar settings. Future studies using probability or multisite sampling are recommended to improve representativeness. Another limitation is the lower internal consistency of the non-user subscale ($\alpha = 0.642$). This likely attenuates the observed associations for that subgroup and may contribute to weaker or non-significant effects. Findings for non-users should therefore be interpreted with caution, and future work should refine the measurement items or increase the sample size to improve reliability.

Longitudinal designs can track how experience shifts the roles of ease, usefulness, and ethics over time. Experiments can test the effects of prompting curricula and instructor modeling on intention and achievement. Multisite studies can examine policy and culture as moderators of social influence and ethics.

Conclusion

This study examined the acceptance of AI tools in programming education using an extended Technology Acceptance Model. Perceived usefulness and social influence were the strongest positive predictors of intention to use AI tools. Ethical awareness was negatively associated with intentions. Ease of use and programming experience correlated with key perceptions but did not add independent predictive power to the full model. Users and non-users differed in several aspects. Usefulness and ease were mapped to users' intentions, whereas non-users showed weak or no links without direct experience.

These findings suggest a simple and practical rule. Instructors should model responsible workflows and verification steps. Programs should provide disclosure rules, credit guidance, and prompt support. These actions can increase perceived usefulness and strengthen social cues while reducing integrity risks that suppress intention.

The non-user scales showed moderate reliability and may require further refinements. Future studies should test longitudinal changes as students gain more experience. Trials comparing prompting curricula, ethics training, and instructor modeling can identify causal levers. Multisite studies can examine how policy and culture shape the roles of usefulness, social norms, and ethics. The findings of this study point to a balanced approach that combines value, guidance, and safeguards so that AI can support programming education without undermining learning or integrity.

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Ethics

All participants were informed of the study aims,

procedures, risks, and benefits, and provided written informed consent prior to participation. Participation was voluntary, with the option to withdraw at any time, without penalty. Confidentiality was maintained by assigning coded identifiers, storing data on secure password-protected systems, and reporting only aggregate results so that individuals could not be identified. This study adhered to the principles of the Declaration of Helsinki and complied with the applicable institutional and national research ethics guidelines.

Participation was voluntary and anonymous. Incentives were not offered. Institutional ethical approval was obtained prior to data collection.

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