Generative AI in Programming Education: Insights into Student Satisfaction and Sustainable Adoption in Indonesian Higher Education

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***Abstract*— The rapid evolution of generative AI technologies has started to automate coding instructions through code generation, step-by-step guidance, and real-time feedback. These capabilities stand to gain significantly in learning outcomes optimization and educational experience customization. However, the adoption and continued use of such sophisticated technologies, particularly in emerging economies like Indonesia, raised profound concerns about the availability, suitability, and sustained use of these tools over time. This study intends to evaluate the factors influencing learners' satisfaction and their continued intention in using generative AI technologies in programming courses. The study uses the Technology Acceptance Model and Expectation Confirmation Model to examine satisfaction relations and continuance intention with a focus on several variables: compatibility, self-efficacy statement, technology readiness, efficiency, perceived ease, usefulness of the technology, and other relevant constructs. Data will be collected through a structure questionnaire, which will be distributed to a diverse sample of students. Data will then be analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results of this research are anticipated to be useful in the success and sustainable fostering of generative AI applications in educational settings.**

Keywords*— *Generative AI, Artificial Intelligence, Programming, Education, Satisfaction, Continued Use Intention, Indonesia, University Students

I. Introduction

Generative AI has undeniably transformed the domain of education, particularly the attainment of learning objectives associated with computer programming. Students interact with AI-powered code generators and other coding assistants which provide real-time intervention and support with complex programming tasks, thereby enhancing personalized learning opportunities [1], [2]. These tools also boost engagement, learning outcomes, and problem-solving skill development necessary for programming [3]. As rational as these advances might seem, the effectiveness of AI education technologies, and learning tools in particular, remains unexamined in many countries, especially in the case of emerging economies like Indonesia, which suffers from stark AI education and digital literacy gaps [4], [5].

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This research is important as it promotes an increase in the supply of programmers by improving teaching methods and techniques. Understanding how generative AI can assist learning is pivotal for the development of educational policies and frameworks, especially as new technologies emerge [6]. Even with a growing interest, there is a lack of understanding regarding what drives student satisfaction and perpetual engagement with generative AI applications in programming education [7]. Very few have ventured into the affects of AI in teaching programming, particularly in developing countries like Indonesia. In the recent literature, there are significant gaps of concern regarding generative AI in programming education. Liu and Li [1] note an important gap concerning the effectiveness of the interaction between AI and humans, highlighting especially pair programming case. Sun et al. [8] contend that while such tools could affect a student's engagement with the material, AI does not fundamentally enhance performance. Yan et al. [9] discuss the gaps directing the use of generative AI for optimized engagement strategy planning towards pre-defined targets and mention individual differences and task complexity as problems. Kim [10] notes gaps concerning students' unfavorable attitudes towards AI tools, he contends that radical and experience-based learning strategies must be employed. For this reason, Kim et al. [11] also argue about the simplicity of strategic AI integration into programming pedagogy. They discuss the shortage of research-based reasoning for the development of such frameworks to guide implementation.

This study hopes to investigate the generative AI's impact on programming education, specifically in higher education institutions within Indonesia. It hopes to add value by analyzing literature and determining what motivates students, particularly in their satisfaction with generative AI tools, to continue using them.

II. Literature Review And Hypothesis Development

A. Expectation Confirmation Model

Analyze user behavior and continued use intention in information systems (IS) as well as in technology adoption is known as ECM. The model proposes that the primary determinants of system or service satisfaction are its usefulness and satisfaction associated with its use [12], [13]. Since ECM examines how people behave after they've adopted new tools or methods, it's especially useful for understanding why generative AI continues to be used over time in teaching and instructional design.

B. Technology Acceptance Model

Originally formulated in 1985 by Davis, this model attempts to forecast the user's acceptance and readiness to use new information systems. This model consists of two parts: perceived usefulness (PU) and perceived ease of use (PEOU) [14]. TAM claims that technology are more likely to be adopted if it helps achieve an increase in their performance and is simple to use [15]. A greater number of studies conducted over the years have validated TAM's claims throughout different disciplines, confirming its ability to pinpoint the factors that affect the adoption decisions made by users [16].

C. Compatibility (C)

Compatibility refers to the extend in which an innovation is perceived to be align with the adopter's existing sociocultural values, prior experiences, and their current needs [17]. In the opinion of Yu et al [18], they found that university students who had more positive perceptions of ChatGPT with regard to its compatibility with their learning patterns had much fewer operational problems with the system, enhancing their perceived ease of use.

H1. Compatibility positively impact towards Perceived Ease of Use.

D. Self-Efficacy (SE)

Individual's confidence to carry out certain actions, which results in desired achievements is called Self-Efficacy [19]. It encompasses the confidence in one's control over motivation, behavior, and the social environment. A study by Falebita and Kok [20], technological self-efficacy positively and significantly affects PEOU perception among undergraduates. The research showed that the students' self-efficacy influenced the way they perceived the AI tools as easy or difficult to use.

H2. Self-efficacy positively impact towards Perceived Ease of Use.

E. Technological Readiness (TR)

Technological Readiness refers to preparedness level, attitude, and skills of an individual has concerning technology adoption [21]. In support of the findings by Falebita and Kok [20] asserted that readiness affects technological self-efficacy level, which means that readiness enhances people's belief in their ability to productively apply AI tools. Besides, as willingness and intention to accept and make use of technology increases, they, in turn, will automatically improve the attitude toward seeing the device as intuitive or user-friendly. Readiness regarding technology also enhances perceived usefulness, which explains that people who are technologically prepared will most likely appreciate AI tools designed for academic-related tasks and productivity enhancement.

H3. Technological readiness positively impact towards Self-Efficacy.

H4. Technological readiness positively impact towards Perceived Ease of Use.

H5. Technological readiness positively impact towards Perceived Usefulness.

F. Efficiency (E)

Efficiency indicates measurable productivity in relation to input. In other words, time, effort, and cost should all be minimized in resource usage [22]. Yu et al. [18] cited that perceived usefulness is deeply affected by efficiency. This suggests that for students who view ChatGPT as a sophisticated answering machine capable of multitasking, their performance is enhanced, which makes them consider it useful for academic tasks.

H6. Efficiency positively impact towards Perceived Usefulness.

G. Perceived Ease of Use (PEOU)

Perceived Ease of Use, which is defined as the amount of effort an individual perceived to be necessary in the usage of a specific technology. PEOU became popular through the work of Davis [22]; this construct points out that any technology that is easy to use will be adopted. Falebita and Kok [20] further proved this by demonstrating that PEOU significantly and positively impacts Perceived Usefulness. Their findings suggest that students who rate AI tools as user-friendly also deem them as useful AI applications designed for completing academically oriented tasks, illustrating the usefulness of usability in technology acceptance. Building upon this foundation, Yu et al. [18] further established that PEOU enhances the perceived usefulness of a system while also significantly impacting user's satisfaction and their intent to continue using the system. Moreover, it was shown that PEOU positively impact students' intention to keep using the tool, which suggests that ease of use serves as a predictor of continued usage.

H7. Perceived Ease of Use positively impact towards Perceived Usefulness.

H8. Perceived Ease of Use positively impact towards users' Satisfaction.

H9. Perceived Ease of Use positively impact towards Continued Use Intention.

H. Perceived Usefulness (PU)

Perceived Usefulness (PU) is the degree in which an individual appreciates a technology's capability in enhancing the performance of a task [22]. With respect to ChatGPT, Yu et al. [18] noted that perceived usefulness is important in determining user satisfaction and system use retention. In particular, PU had a significant and positive impact towards satisfaction, which indicates that students who perceived ChatGPT as beneficial in achieving academic milestones were more satisfied with the tool. Further, Yu et al. [18] argued that PU positively influences Continued Use Intention, meaning that users will tend to continue using ChatGPT if it is believed to enhance their learning performance.

H10. Perceived Usefulness positively impact towards Satisfaction.

H11. Perceived Usefulness positively impact towards Continued Use Intention.

I. Satisfaction (S)

Satisfaction in technological usage describes the fulfillment of expectations by a system's performance and features [23]. As noted by Yu et al. [18], satisfaction is significant when attempting to assess user's continued intention of a system, and is also a focal variable that is delimited by others, like the usefulness of the information provided. In other words, if a user achieves positive outcomes with the use of ChatGPT tools, then satisfaction increases the likelihood of smooth incorporation of the device into everyday routines.

H12. Satisfaction positively impact towards Continued Use Intention.

J. Continued use intention (CI)

According to ECM, a individual's intention to continue using a technology are directly linked to their satisfaction and perception of a service, which is largely driven by the technology's performance and expectations [24]. In Yu et al. research [18], use intention is articulated as a decision made by a user exercising sufficient thought and deliberation about a particular system or technology to voluntarily plan to keep using it. Alongside the rationale provided throughout the whole paper as a reasonably taken decision about interaction(s) in the future with the technological system, the intention described caught attention regarding the focus on AI, including ChatGPT, and its application in higher education. This emerged from a survey whose results showed that intended continuance had been heavily influenced by several major elements. User satisfaction proved, to the greatest extent, to be the strongest predictor: when people are satisfied with a system, they tend to try to use it repeatedly in the future.

In this study, we propose a model to asses the relationships of Technological Readiness, Compatibility, Self-Efficacy, Perceived Ease of Use, Efficiency, Perceived Usefulness, Satisfaction, and Continued Use Intention. Their intricate relationships were analyzed quantitatively as can be seen in Figure 1.

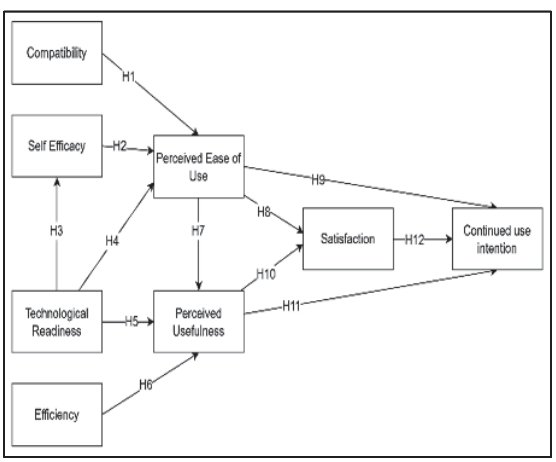

Fig 1. Research Model

III. Research Methodology

A. Measurement Instrument

A survey-based methodology was employed to investigate the influence of generative AI in the programming education of Indonesia's university students. For this, a survey was designed to capture "satisfaction" and "continued usage" constructs of generative AI integrated within programming education. Every measurement instrument was developed to capture enabling factors of students' experiences with Generative AI in programming. The Expectation Confirmation Model (ECM), Technology Acceptance Model (TAM), and other relevant models were utilized in the Literature review. The instrument includes many constructs such as compatibility, self-efficacy, technological readiness, perceived level, usefulness, efficiency, satisfaction, and intention towards continued use.

B. Data Collection Procedure and Sample

This research conducts a survey and derives data using an online questionnaire facilitated by Google Forms to reach a broad sample of University Students. Data collection will take 4-8 weeks. To maintain a high standard of data, all responses that are not complete or are contradictory will be discarded prior to analysis. The population of interest is university students in Indonesia who have utilized generative AI applications for programming tasks. There will be no random sampling; hence, non-probability sampling will be utilized through convenience sampling, where willing and available participants are sought. Social media will be used to disseminate the survey link and maximize participation. Total confidentiality concerning their responses will be provided to participants, and informed consent will be acquired prior to survey commencement.

C. Data Analysis Technique

To evaluate the data, the PLS-SEM method using the SmartPLS software will be employed. The data and the model's complexity are factors that aid in choosing PLS-SEM. PLS-SEM is utilized here, as it can handle the analysis of several latent variables and their relations, which is useful in studying the adoption of Gen AI in programming education. By using this method, other effects such as mediation can be studied, allowing for more complex models that explore the indirect relations among the variables in the model. This deepens the understanding of the relationships that exist and explains the important relationships in the model that emerge from a close examination of the data using simpler methods.

IV. Result & Discussion

Among the 407 respondents, 379 were analyzed, and were included in the analysis that met the inclusion criteria that respondents had programming experience, used Generative AI before, and are currently in college as active students. Findings reveal that all participants (100%) with prior programming experience had experience using Generative AI tools like ChatGPT, Deepseek, Gemini, and Claude, majority (61%) have used these tools for 1 to 3 years and (39%) for less than a year, this may be attributed to the recent nature and quick adaptation of these technologies. The gender composition was fairly even (52% female, 48% male), and almost all (99%) were between the ages of 17–27. Most were undertaking a Bachelor's degree (85%), followed by diploma holders (14%). Only one participant was undertaking a Master's degree. Adoption by academic year distribution showed that the rate of adoption was higher among second-year and third-year students (35% and 38%), while fourth-year (18%) and first-year (9%) students were fewer. Geographically, participants were mostly from Java—DKI Jakarta (35%), West Java (34%) and Banten (29%) and with little representation from other provinces.

TABLE I. Respondent Demographic

Profile	Category	Frequency	Percentage
Have you ever used Generative AI (ChatGPT, Deepseek, Gemini, Claude, etc.)?	Yes	379	100%
	No	0	0%
	Total	379	100%
How often do you use Generative AI (ChatGPT, Deepseek, Gemini, Claude, etc.)?	1 to 3 years	233	61%
	Less than 1 year	146	39%
	More than 3 years	0	0%
	Total	379	100%
Gender	Male	182	48%
	Female	197	52%
	Total	379	100%
Age	17 - 27 years	377	99%
	28 - 43 years	2	1%
	44 - 59 years	0	0%
	Total	379	100%
Current or Highest Education Level	Diploma	54	14%
	Bachelor's Degree	324	85%
	Master's Degree	1	0%
	Total	379	100%
Academic Year	1st Year	33	9%
	2nd Year	133	35%
	3rd Year	143	38%
	4th Year	70	18%
	Total	379	100%
Province of Residence	Banten	109	29%
	DKI Jakarta	134	35%
	West Java	130	34%
	Central Java	2	1%
	East Java	2	1%
	Papua	1	0%
	Riau	1	0%
	Total	379	100%

Convergent Validity presented on table II, Hair et al. outline the examination of the outer loadings, CR, and AVE as the primary methods utilized to determine convergent validity [25]. For outer loadings, most values exceeding 0.70 are interpreted as indicating high-item reliability. Items, such as Compatibility (0.817–0.849) and Self-Efficacy (0.845–0.871) on the extreme end, and even PEOU1 (0.710) and PU1 (0.709) on the lower end, are all deemed acceptable. For all constructs, the CR values were over 0.79, which is above the minimum 0.70 level of internal consistency. The AVE also displayed a high amount of internal consistency, with its values ranging from 0.520 (Perceived Ease of Use) to 0.733 (Self-Efficacy) which also meets the minimum 0.50 level. Therefore, the results in sum reinforce the measurement model does convergent validity which means the constructs are adequately represented by their indicators.

TABLE II. Convergent Validity

Items	OuterLoadings	CR	AVE
C1	0.848	0.904	0.702
C2	0.849		
C3	0.838		
C4	0.817		
CI1	0.763	0.881	0.597
CI2	0.773		
CI3	0.826		
CI4	0.773		
CI5	0.726		
E1	0.751	0.793	0.562
E2	0.723		
E3	0.774		
PEOU1	0.710	0.813	0.520
PEOU2	0.722		
PEOU4	0.728		
PEOU5	0.724		
PU1	0.709	0.832	0.553
PU2	0.757		
PU3	0.788		
PU4	0.717		
S1	0.828	0.870	0.626
S2	0.780		
S3	0.807		
S4	0.746		
SE1	0.860	0.932	0.733
SE2	0.858		
SE3	0.845		
SE4	0.847		
SE5	0.871		
TR1	0.800	0.887	0.612
TR2	0.793		
TR3	0.784		
TR4	0.797		
TR5	0.737		

TABLE III. Discriminant Validity

	C	CI	E	PEOU	PU	S	SE	TR
C								
CI	0.441							
E	0.575	0.578						
PEOU	0.505	0.472	0.786					
PU	0.506	0.292	0.538	0.519				
S	0.491	0.429	0.642	0.711	0.308			
SE	0.46	0.35	0.455	0.489	0.3	0.268		
TR	0.556	0.306	0.502	0.475	0.525	0.313	0.136	

The assessment of discriminant validity in this research utilized the HTMT method instead of other methods of assessment such as Fornell-Larcker criterion and cross-loadings which are less reliable as argued by Henseler, Ringle, and Sarstedt [26]. According to the HTMT method, values below 0.90 indicate adequate discriminant validity. The table presented shows HTMT values below the required threshold of 0.90. The Perceived Ease of Use and Efficiency constructs had the highest value ascribed to them (0.786) followed by Perceived Ease of Use and Satisfaction (0.711). The constructs are related in theory, however, the values are above 0.5 confirming empirical uniqueness. The Self-Efficacy and Technological Readiness pair had the lowest HTMT 0.136, which means that the discriminant validity of the constructs are fully supported.

TABLE IV. Path Coefficient

Hypothesis	Path	St Dev	t-value	p-value	Decisions
H1	C -> PEOU	0.062	2.299	0.011	Accepted
H2	SE -> PEOU	0.052	5.728	0.000	Accepted
H3	TR -> SE	0.051	2.393	0.008	Accepted
H4	TR -> PEOU	0.052	5.095	0.000	Accepted
H5	TR -> PU	0.059	4.912	0.000	Accepted
H6	E -> PU	0.060	2.778	0.003	Accepted
H7	PEOU -> PU	0.059	3.008	0.001	Accepted
H8	PEOU -> S	0.042	12.255	0.000	Accepted
H9	PU -> S	0.047	1.005	0.158	Rejected
H10	PU -> CI	0.049	2.045	0.020	Accepted
H11	PEOU -> CI	0.057	3.950	0.000	Accepted
H12	S -> CI	0.051	4.213	0.000	Accepted

In structural equation modeling, a p-value is less than 0.05, and t-value is greater than 1.96, is required to consider a variables' relationship as significant ,this is supported on the 95% confidence level [25]. Under these conditions, eleven hypotheses (H1–H8 and H10–H12) were accepted, and one hypothesis (H9) were rejected as its p-value was greater than the required 0.05. It can be inferred from this result that almost all the proposed paths were confirmed, except the one from Perceived Usefulness to Satisfaction, which was non-significantly tested.

The results indentified that Perceived Ease of Use was positively influenced by Compatibility and Self-Efficacy (H1, H2), suggesting that affirmation of learning and technological self-confidence helps to declutter the learning process [18], [20]. Technological Readiness positively impacts Self-Efficacy, Perceived Ease of Use, and Perceived Usefulness (H3–H5), emphasizing its importance in improving Self-Efficacy, Ease of Use, and Usefulness recognition [20]. Efficiency also impact Perceived Usefulness positively (H6), supporting the claim that appropriate assistance enhances value [18]. In line with the Technology Acceptance Model, Perceived Ease of Use impacted Perceived Usefulness, Satisfaction, and Continued Use Intention (H7, H8, H11) with emphasis on adoption effectiveness [18]. Perceived Usefulness Satisfaction (H9 rejected) indicating satisfaction relies more on usability than utility [27] but did predict Continued Use Intention (H10) [18]. Satisfaction also polarised Continued Use Intention (H12) which confirms that positive experiences must be defended and maintained in order to ensure continued adoption [18]. In the end, perceived ease of use, readiness and satisfaction were determined to be the strongest predictors of continued usage. As for perceived usefulness offered more support for continuance than satisfaction.

V. Conclusion

This research investigates generative AI usage in programming education in Java-Indonesia to determine the factors influencing student's satisfaction and continued intention at Indonesian universities. We also find that generative AI tools are pervasive, since a majority of respondents have programming experience and regular use of platforms including ChatGPT, Deepseek, Gemini, and Claude. Structural equation modeling results verified that the continued usage was directly determined by perceived ease of use, perceived usefulness and satisfaction, and satisfaction was the strongest factor influencing continued usage. Ease of use also enhanced both usefulness and satisfaction, reinforcing its central role in adoption. The analysis reveals that perceived usefulness did not influence satisfaction significantly. Students favored integration of usability and learning systems function over usability as ways of enhancing experiences . This evidence furthers the literature on AI integration in education and the specific barriers to its use in emerging markets, like Indonesia. It reaffirms the need for AI in education to be designed with usability, confidence, and alignment with students goals. The evidence reveals the need for the development of artificial intelligence (AI) curricula tailored specifically for teaching prerequisites of AI training and digital literacy enhancement. These curricula should incorporate ethical modules aimed at the development and mitigation of generative AI biases, such as reliance and misuse. In the distant future, generative AI appears to be very powerful for programming education, but the lasting effects will be determined by thoughtful user experience design and meticulous onboarding.

VI. Limitation & Further Study

This research has offered some useful contributions, but it has also suffered from some limitations. For example, the participants were university students from Indonesia, specifically from Java, thus limiting the applicability of the results to other regions with different technological and educational systems. Moreover, the research adopted a cross-sectional design, which gazes at perceptions at one time point only, which does not capture the trajectory of behavior across time or changes in behaviors given attitudes and AI. Furthermore, the present study was focused on students' perceptions and did not take into consideration other key stakeholders, such as teachers, decision makers, or administrators of the institutions, whom are fundamental when talking about the integration of AI. Future study should focus more on characteristics of the system's evolution and continued use, in particular where cross-disciplinary regional or longitudinal methods and approaches to real-world and normative applications are used. The perspective of educators and institutions, particularly policy makers, are essential when designing holistic approaches to ensure that generative AI is used to its full potential and becomes integrated in a sustained way in the AI and programming curriculum.

Acknowledgment

This work is supported by Research and Technology Transfer Office, Bina Nusantara University with initiative project number PP0030079. T.E. Tandra, C.L. Rosadi and N.K. Ningtji writing paper. A. Gui and E. Halim review and editing. Thanks to Nguyen Minh Tuan as corresponding author (minhtuan@ptit.edu.vn). Data can be found at https://zenodo.org/uploads/17812435.

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