Generative AI Use Patterns and Ethical Dilemmas among Pre-Service Teachers

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ABSTRACT

Generative Artificial Intelligence (GenAI) is increasingly embedded in higher-education learning, offering efficiency while raising questions about the boundary between technological assistance and delegation of thinking. This study explores GenAI-use patterns, ethical dilemmas, and cognitive engagement among pre-service teachers. An exploratory qualitative study involved 24 second-semester Informatics Engineering Education students selected purposively. Over six weeks, data were collected through semi-structured interviews, three focus-group discussions, classroom observations, and reviews of task artifacts and prompt histories. Thematic analysis involved familiarization, coding, category development, theme construction, and cross-source comparison. Three patterns emerged: Cognitive Partner (6 students; 25.0%), Practical Adaptor (13; 54.2%), and Passive Outsourcing (5; 20.8%). Eighteen students (75.0%) interpreted the absence of an explicit lecturer prohibition as implicit permission to use GenAI, while 16 (66.7%) reported anxiety about possible misclassification by AI detectors. The findings show that educational implications depend less on frequency of use than on verification, independent revision, and students' retention of cognitive responsibility. Teacher education should therefore frame GenAI as cognitive support, clarify task-specific boundaries, and require accountable verification rather than allow AI to substitute for learning.

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1. Introduction

Generative Artificial Intelligence (GenAI) has become embedded in students' academic practices, from idea exploration and concept explanation to drafting and programming support. Accordingly, the central question is no longer simply whether students use GenAI, but how they position it within the learning process. Cena et al. (2026) show that students perceive GenAI simultaneously as an opportunity and a risk, making control over the thinking process a central issue in its educational use.

The educational value of GenAI depends substantially on students' capacity to maintain self-regulation. Xu et al. (2025) emphasize the importance of metacognitive support in helping students plan, monitor, verify, and evaluate their learning. From a constructivist perspective, GenAI can support knowledge construction when it extends understanding rather than replaces students' intellectual activity (Alam et al., 2026). Prompting, comparing responses, and revising outputs can also constitute epistemic work that supports GenAI literacy (Sofkova Hashemi, 2026; Yan et al., 2025). Thus, the quality of GenAI use is better judged by the cognitive processes that remain under students' control than by frequency of use alone.

The issue becomes more sensitive when GenAI is used for tasks intended to represent students' academic competence. Gruenhagen et al. (2024) and Hadinejad et al. (2025) show that students do not always draw the same boundary between acceptable assistance and substitution of intellectual contribution. This uncertainty is compounded by variation in institutional policies and guidance (Moorhouse et al., 2023; Wang et al., 2024). Jin et al. (2025) and Tsao (2025) further indicate that GenAI policies are not merely formal documents; they are interpreted and enacted by users. Consequently, the absence of explicit rules can create an ethical interpretive space at the classroom level.

This issue has particular consequences for pre-service teachers. They must not only be able to use AI, but also justify its pedagogical purpose, define appropriate limits, recognize risks, and remain accountable for outcomes. Dayagbil et al. (2025) show that pre-service teachers acknowledge both the potential and limitations of AI, while Kohnke et al. (2026) stress the need to integrate AI literacy, privacy, academic integrity, and pedagogical strategy into teacher education. Seufert et al. (2025) and Prilop et al. (2025) likewise connect technological competence with critical evaluation and responsible pedagogical decision-making. In Indonesia, related studies have addressed digital-literacy challenges among pre-service teachers (Tangkearung et al., 2026) and the use of AI-supported problem-based learning in relation to undergraduate critical thinking and academic performance (Syamsuddin et al., 2025).

Research on GenAI in higher education has examined perceptions, benefits, risks, policy, and user readiness, yet a process-level explanation remains limited: how do pre-service teachers distribute cognitive responsibility between themselves and AI across different tasks? Borzanović et al. (2026) show that students weigh educational benefits against ethical risks and dependency, whereas Lindkvist et al. (2026) demonstrate that students may deliberately restrict GenAI use when it conflicts with learning goals. These findings underscore the need to examine AI-use decisions through verification, revision, delegation, and ethical judgment.

This study explores GenAI-use patterns among Informatics Engineering Education students completing programming, academic writing, and instructional-design tasks. It focuses on variations in cognitive engagement, delegation of cognitive processes, and the ethical dilemmas accompanying GenAI use. Its novelty lies in identifying three typologies—Cognitive Partner, Practical Adaptor, and Passive Outsourcing—and in conceptualizing implicit permission as the tendency to interpret the absence of an explicit prohibition as legitimate authorization to use AI. The study aims to explain these patterns and derive implications for teacher education that preserves students' cognitive and professional responsibility.

2. Research Method

Research Design

This study employed an exploratory qualitative approach. The design was selected because the study did not seek to test effectiveness or causal relationships; instead, it examined patterns of GenAI use, students' reasoning when using the technology, and ethical dilemmas arising in learning activities. The unit of analysis comprised participants' experiences, practices, and interpretations of GenAI use in academic tasks.

Participants

The study involved 24 second-semester students in the Informatics Engineering Education Study Program, Faculty of Engineering and Vocational Education, Universitas Pendidikan Ganesha. Participants were selected purposively based on the following criteria: active student status; use of at least one large-language-model-based GenAI platform for academic purposes during the previous four weeks; GenAI use at least once per week; and willingness to participate in interviews, focus-group discussions, observations, and artifact review. The minimum threshold of weekly use allowed the study to capture variation between intensive and occasional users.

Table 1. Participant Characteristics

Characteristic	Category	n	Percentage
Participants	Semester II	24	100.0%
Gender	Male	12	50.0%
	Female	12	50.0%
Age	18 years	5	20.8%
	19 years	15	62.5%
	20 years	4	16.7%
GenAI frequency	Daily	8	33.3%
	3–5 times per week	12	50.0%
	1–2 times per week	4	16.7%
Dominant task domain	Programming and algorithms	11	45.8%
	Academic writing and theory	8	33.3%
	Curriculum and pedagogy	5	20.8%

Research Instruments

Data were collected using a semi-structured interview guide, a focus-group discussion guide, an observation sheet, and an artifact-review sheet. The interview guide examined participants' experiences with GenAI, reasons for using AI for particular tasks, verification practices, forms of revision, understandings of ethical boundaries, and responses when lecturers did not explicitly state AI-use rules. The focus groups used dilemma cases to elicit participants' reasoning behind AI-use decisions. The observation sheet recorded prompting patterns, verification, movement between AI and other sources, and revisions to AI outputs. The artifact-review sheet compared prompt histories with the submitted academic products.

Table 2. Research Instrument Focus

Instrument	Focus	Main question/indicator
Semi-structured interview	Use patterns and verification	How do you use GenAI when completing an assignment, and what do you do after receiving its response?
Focus-group discussion	Ethical dilemmas	Is GenAI use still acceptable if the lecturer provides no explicit rule? Explain your reasoning.
Observation	Cognitive engagement	Prompting patterns, response checking, use of comparison sources, and independent revision.
Artifact review	Contribution to the final product	Changes between the initial GenAI output, the revision process, and the final academic product.

Data Collection Procedure

Data were collected over six weeks. All participants completed individual interviews lasting 30-45 minutes, followed by three focus-group discussions involving eight students each and lasting 60–90 minutes. Observations were conducted during learning activities in which digital-device use was permitted. The researchers also reviewed voluntarily submitted artifacts, including program code, academic-writing drafts, lesson-module designs, and prompt histories. Multiple sources were used to compare participants' accounts with observable GenAI practices across task contexts.

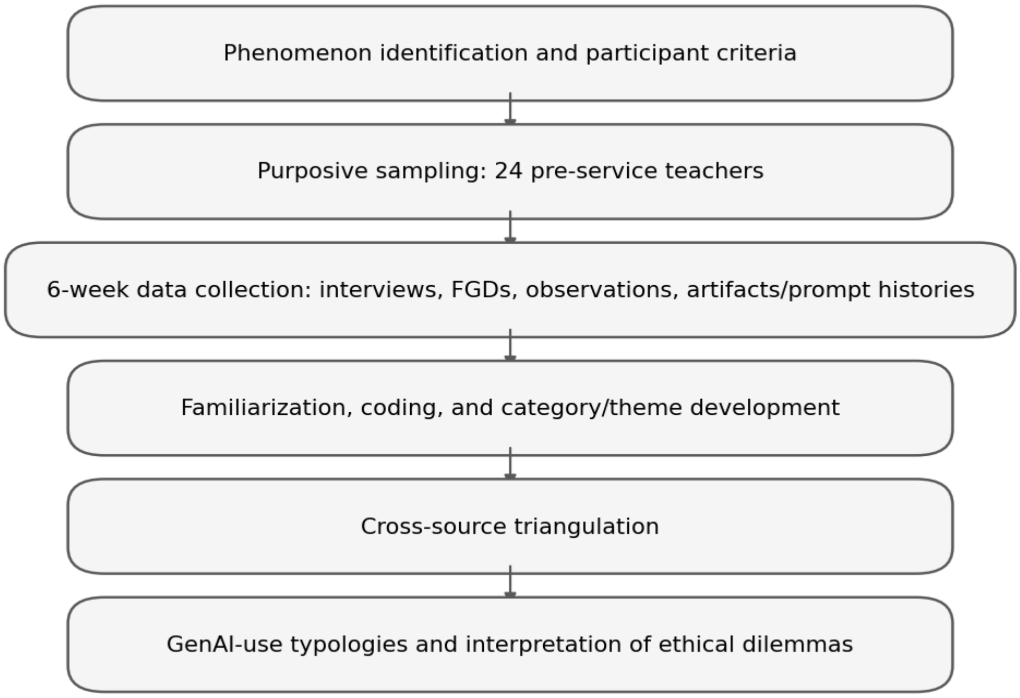

Figure 1. Research flow

Data Analysis

Data were analyzed thematically and iteratively across four sources: interviews, focus-group discussions, observations, and task artifacts. After transcription and familiarization, data units were coded according to the purpose of GenAI use, verification practices, extent of independent revision, degree of cognitive delegation, and ethical considerations. Conceptually related codes were grouped into analytical categories and then challenged through cross-source comparison. This comparison assessed whether participants' accounts were consistent with observed practices and with traces of change in their artifacts. The typologies were derived from dominant configurations across these dimensions rather than from frequency of use alone. Accordingly, Cognitive Partner, Practical Adaptor, and Passive Outsourcing were treated as contextual patterns rather than fixed individual traits; the same participant could display a different pattern as task demands changed.

Interpretive depth was strengthened by examining both convergence and tension across sources before themes were finalized. Findings were not inferred from isolated quotations or a single data type, but from recurring patterns supported across sources. Credibility was enhanced through source triangulation, researchers' reflexive notes, analytical discussions used to challenge initial interpretations, and member checking of summary findings with selected participants. Analytical discussion was used to strengthen reflexivity and interpretive rigor rather than to calculate intercoder agreement. Participants were anonymized using codes P01–P24, participation was voluntary, and participation was not linked to course grades. Participant quotations are presented in English translation.

3. Results

The analysis identified variation in GenAI-use patterns based on how students verified AI outputs, revised them, retained control over the thinking process, and defined acceptable boundaries of use. Three principal typologies emerged: Cognitive Partner, Practical Adaptor, and Passive Outsourcing. Cross-cutting themes included implicit permission, tension between efficiency and meaningful learning, the professional-role dilemma of pre-service teachers, and anxiety about AI detectors.

Patterns of Generative AI Use in Learning

All participants used ChatGPT to support at least one academic activity. Fifteen students (62.5%) also used Perplexity or Consensus to locate sources, while 11 (45.8%) used Claude primarily to support code development and debugging. Eight students (33.3%) used GenAI daily, 12 (50.0%) used it three to five times per week, and four (16.7%) used it one to two times per week.

Table 3. Participants' Patterns of Generative AI Use

Aspect	Category	n	Percentage
Platform	ChatGPT	24	100.0%
	Perplexity/Consensus	15	62.5%
	Claude	11	45.8%
Frequency of use	Daily	8	33.3%
	3–5 times per week	12	50.0%
	1–2 times per week	4	16.7%
Dominant task domain	Programming and algorithms	11	45.8%
	Academic writing and theory	8	33.3%
	Curriculum and pedagogy	5	20.8%

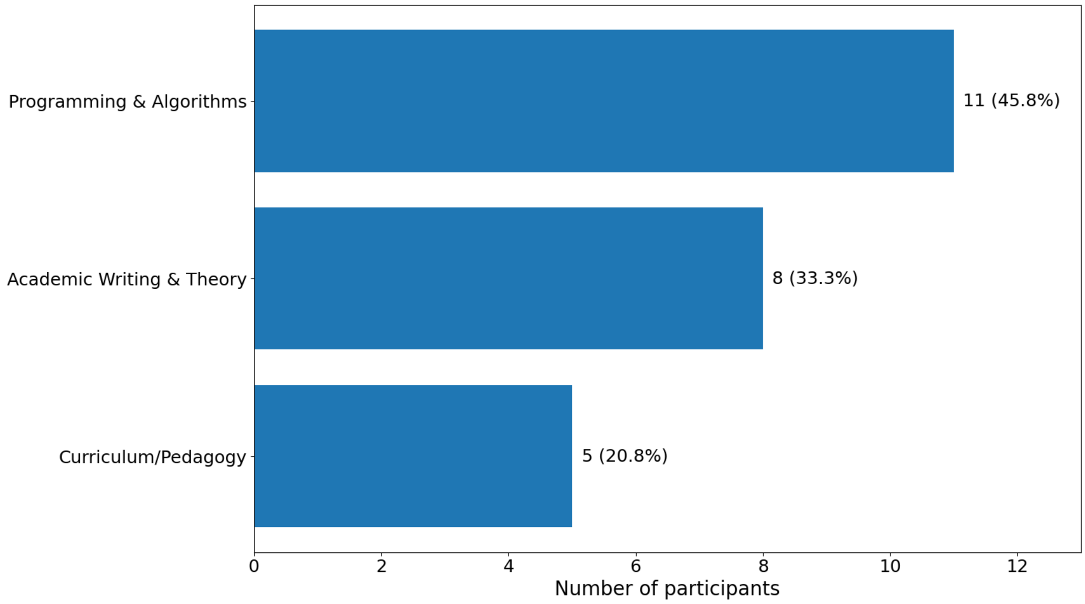

Figure 2. Dominant task domains in GenAI use

Typology of Generative AI Use

Three dominant patterns were identified from the purpose of use, level of verification, extent of independent revision, and degree of cognitive delegation. Six students (25.0%) displayed the Cognitive Partner pattern, 13 (54.2%) the Practical Adaptor pattern, and five (20.8%) the Passive Outsourcing pattern.

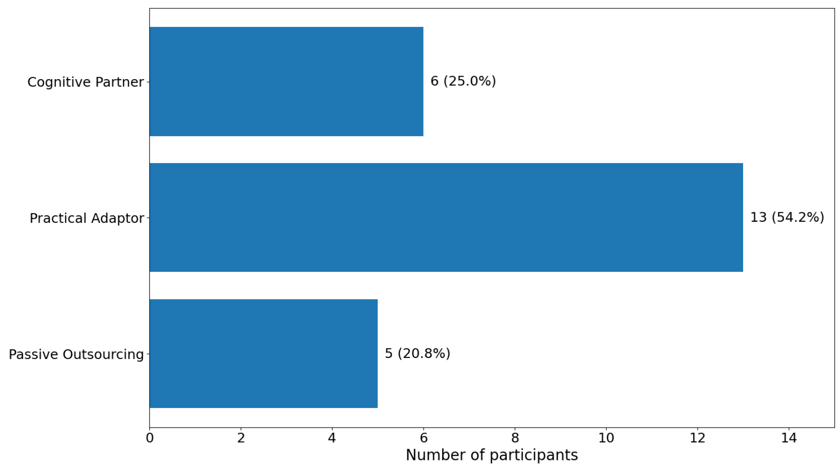

Figure 3. Distribution of Generative AI-use typologies

Table 4. Characteristics of Generative AI-use Typologies

Dimension	Cognitive Partner	Practical Adaptor	Passive Outsourcing
Participants	6 (25.0%)	13 (54.2%)	5 (20.8%)
Role of GenAI	Thinking partner	Practical support tool	Substitute for part of the process
Verification	Systematic	Selective	Minimal
Independent revision	Substantive	Partial	Minimal
Cognitive engagement	High	Moderate	Low
Delegation	Limited	Partial	Dominant

Dimension	Cognitive Partner	Practical Adaptor	Passive Outsourcing
Ownership of outcome	High	Moderate	Relatively low
Ethical orientation	Reflective	Pragmatic	Dependent on prohibition

The radar chart in Figure 4 provides an analytical representation of five typology dimensions. Scores from 1 to 3 are not psychometric measurements; they summarize the operational definitions derived from the analysis, where 1 indicates low intensity, 2 moderate intensity, and 3 high intensity.

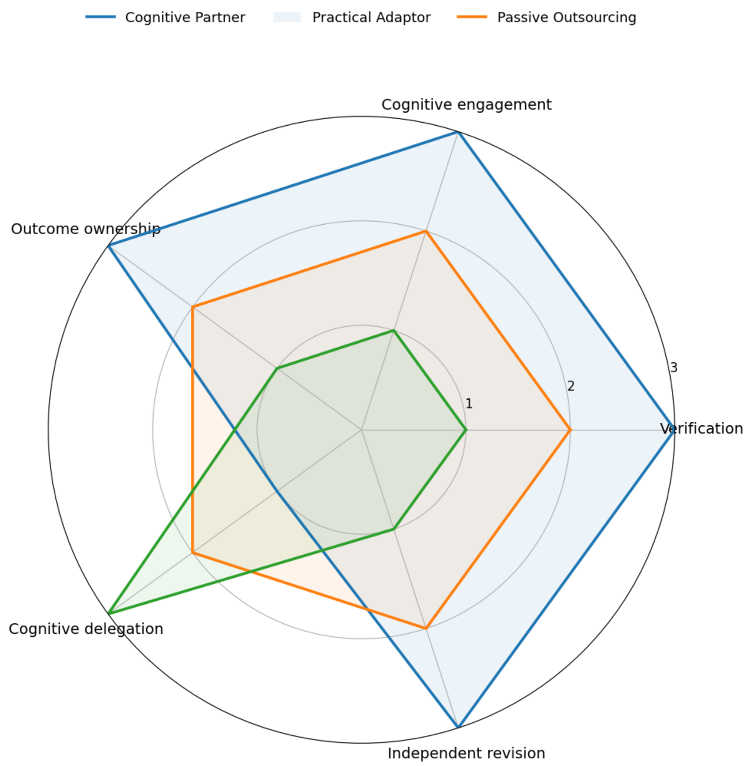

Figure 4. Analytical profiles of Generative AI-use typologies

Cognitive Partner: GenAI as a Cognitive Partner

Students in the Cognitive Partner group used GenAI to extend their thinking. They requested alternative explanations, tested arguments, compared responses with other sources, and modified outputs on the basis of their own understanding. Observation notes showed that these students tended to use iterative follow-up prompts rather than accept the first response.

> *"When I work on a program, I usually ask AI for several possible solutions. Then I check the logic again. If the code runs but I do not understand why, I am not comfortable using it." (P03)*

This statement indicates that GenAI did not remove students' responsibility for understanding. AI functioned as a dialogic resource, while decisions to accept, reject, or modify its responses remained with the student.

Practical Adaptor: GenAI as a Practical Support Tool

Thirteen students displayed the Practical Adaptor pattern. They used GenAI primarily to improve efficiency, for example by generating an initial outline, improving language, assisting with debugging, or simplifying learning materials. After receiving AI output, they adapted it to the task requirements, but verification remained selective.

"I usually ask AI to generate code or an initial outline. Then I look at the parts that fit. If something does not match the lecturer's instructions, I change it. But I do not always check everything from the beginning." (P11)

This pattern reflects partial delegation. Students retained responsibility for the final product while assigning some early stages of the work to GenAI to save time.

Passive Outsourcing: Delegating the Process to GenAI

Five students displayed the Passive Outsourcing pattern. They tended to ask GenAI to produce near-final products and made only limited changes to structure, formatting, or wording. Time pressure and the perception that no explicit prohibition existed recurred in their explanations.

"When the deadline is close, I usually enter the whole question into AI. I choose the answer that seems most reasonable and tidy it up a little. Sometimes I do not have time to check everything because the assignment has to be submitted immediately." (P23)

The finding suggests that learning risk is determined less by the mere use of GenAI than by the extent to which students delegate the thinking processes that the task is intended to develop.

Ethical Dilemmas and the Perception of Implicit Permission

Students could readily identify extreme forms of use, such as submitting an AI-generated answer in full without understanding it. Uncertainty emerged around language editing, paraphrasing, outlining, debugging, and idea generation. Eighteen students (75.0%) interpreted the absence of an explicit prohibition from the lecturer as an indication that GenAI use was acceptable. This study terms this tendency the perception of implicit permission.

"If the lecturer does not say that AI is prohibited, I assume it can be used. Still, I do not think it is appropriate to take an entire assignment directly from AI. I usually consider the type of task and what the lecturer is trying to assess." (P14)

Table 5. Implicit Permission by GenAI-use Typology

Typology	Implicit permission	Participants	Proportion
Cognitive Partner	2	6	33.3%
Practical Adaptor	11	13	84.6%
Passive Outsourcing	5	5	100.0%
Total	18	24	75.0%

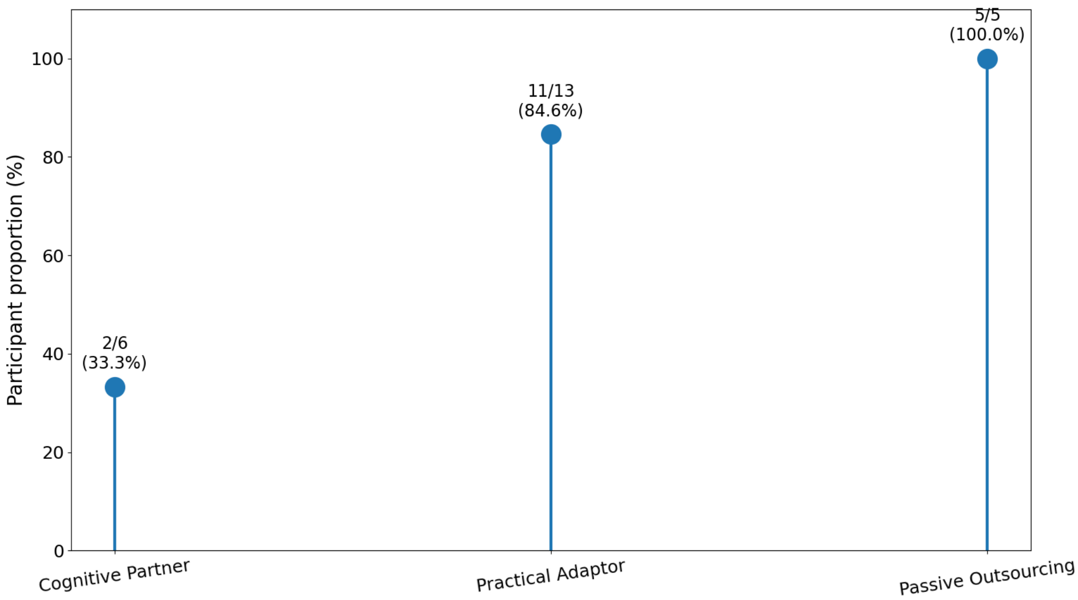

Figure 5. Implicit permission by GenAI-use typology

Tension between Efficiency and Meaningful Learning

Students regarded efficiency as one of GenAI's main benefits. However, some participants recognized that this convenience could alter how they responded to learning difficulties. Cognitive delegation increased most often when tasks were difficult and deadlines were close.

> *"In the past, when my code had an error, I could spend a long time finding the cause myself. Now I sometimes ask AI immediately. It is faster, but I feel that I have become less patient about trying on my own." (P13)*

These findings do not demonstrate a direct decline in cognitive ability. They do, however, indicate a shift in learning strategy when students transfer the search for solutions to AI earlier rather than sustaining independent exploration.

Academic and Professional Role Dilemmas of Pre-Service Teachers

Being pre-service teachers introduced an additional layer of reflection. Participants considered not only how AI helped them complete current assignments, but also how they might later guide their own students in using the technology.

> *"Sometimes I think that, as a teacher, I may ask my students not to depend too much on AI. But I currently use AI almost every day myself. So I need to understand its boundaries from now on." (P09)*

This dilemma shows that GenAI use in teacher education is directly connected to the formation of professional responsibility. Students began to recognize that the ability to use AI must be accompanied by the ability to explain its purpose, define limits, and specify appropriate forms of verification in learning.

Anxiety about AI Detectors and Avoidance Strategies

Sixteen students (66.7%) expressed anxiety about possible misclassification by AI detectors. This concern was not limited to students with high levels of delegation. Some participants reported altering their own writing or using paraphrasing applications to reduce detection scores rather than to improve academic substance.

> *"I once entered writing that I had produced myself into a detector, but the result still indicated possible AI use. After that, I actually changed my own writing so that the percentage would go down." (P05)*

Table 6. AI-Detector Anxiety by Typology

Typology	Experienced anxiety	Participants	Proportion
Cognitive Partner	2	6	33.3%
Practical Adaptor	10	13	76.9%
Passive Outsourcing	4	5	80.0%
Total	16	24	66.7%

Coding and Theme Development

Themes were developed through staged analysis. The researchers reread all data sources, coded segments related to GenAI use, verification, revision, delegation, and ethical considerations, and clustered semantically related codes into analytical categories. The categories were then compared across sources before themes and typologies were finalized.

Table 7. Coding and Theme Development

Data excerpt	Initial code	Analytical category	Theme/Typology
I asked AI to explain it, and then I checked it against the documentation.	Checking AI output	Critical verification	Cognitive Partner
I took the outline and then adapted it to the assignment.	Adapting AI output	Selective adaptation	Practical Adaptor
When time is short, I use the answer that seems most reasonable.	Prioritizing task completion	Dominant delegation	Passive Outsourcing
If the lecturer does not prohibit it, I think that means it is allowed.	Interpreting absence of prohibition as permission	Dependence on external rules	Implicit permission
I am afraid that my own writing will be identified as AI-generated.	Questioning detector accuracy	Evaluation uncertainty	AI-detector anxiety

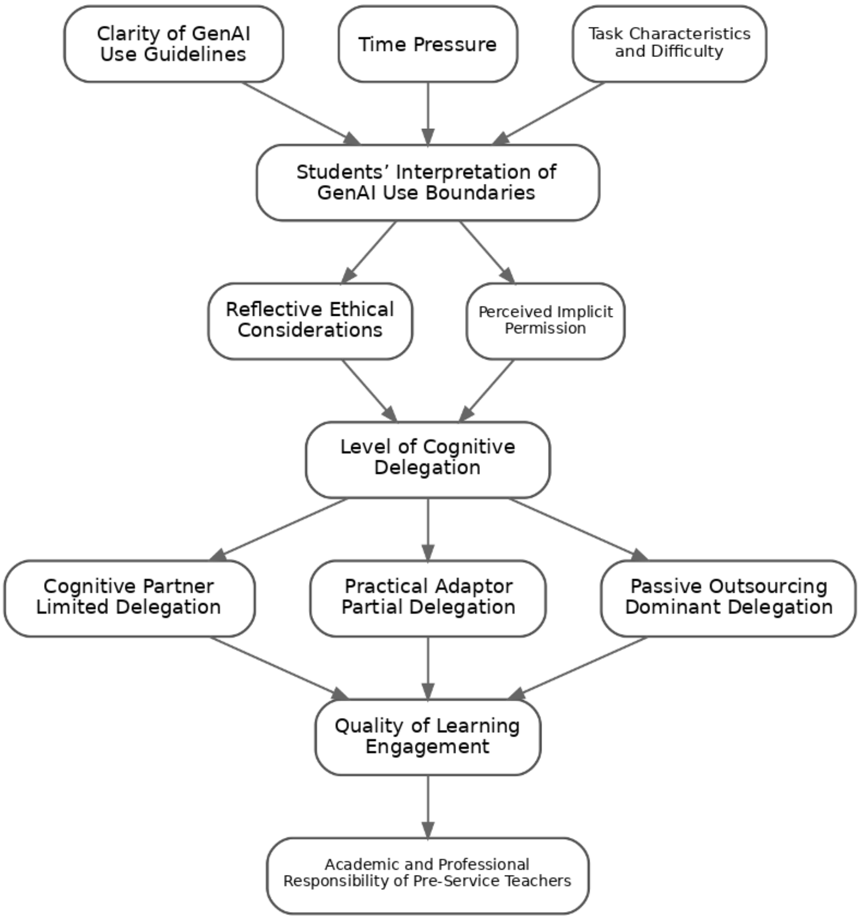

Figure 6. Conceptual model of GenAI-use patterns and ethical dilemmas

4. Discussion

The findings suggest that pre-service teachers' GenAI use is better understood as a spectrum of cognitive delegation than as a binary distinction between use and non-use. The predominance of Practical Adaptors marks an intermediate position: students gain efficiency from GenAI, yet verification and revision are not consistently deep. This extends Silvola et al. (2025), who describe AI use as situationally constructed, by identifying four observable mechanisms through which that variation becomes analytically meaningful: purpose of use, depth of verification, independent revision, and the extent of delegated cognitive work. Frequency alone is therefore an inadequate indicator of learning quality; the more consequential question is whether students retain epistemic control over the rationale, process, and outcome.

The contrast between Cognitive Partner and Passive Outsourcing clarifies this mechanism. In the Cognitive Partner pattern, GenAI functions as a dialogic resource: students seek alternatives, test ideas, consult documentation, and rewrite solutions on the basis of their own understanding. This pattern aligns with Sofkova Hashemi (2026), Yan et al. (2025), and Alam et al. (2026), who frame GenAI interaction as epistemic work and knowledge construction when users remain cognitively active. In Passive Outsourcing, by contrast, efficiency becomes process substitution. When AI immediately takes over as soon as difficulty arises, opportunities to attempt strategies, diagnose failure, and construct understanding are reduced, consistent with Xu et al.'s (2025) emphasis on metacognitive regulation. The present findings do not establish that GenAI directly diminishes cognitive ability; rather, they show that particular forms of delegation can narrow the very processes through which learning is expected to occur.

A second conceptual contribution concerns implicit permission. Most participants interpreted the absence of a lecturer's prohibition as room to use AI. This mechanism is more specific than general ethical ambiguity: the basis for judgment shifts from learning goals and intellectual contribution toward the presence or absence of an external prohibition. The finding extends Hadinejad et al. (2025) and Gruenhagen et al. (2024) on uncertainty over the boundaries of GenAI assistance and adds context to Huang et al. (2025) on the moral dimension of AI-related academic decisions. When rules are not operationalized, students may recognize that submitting an entire AI-generated answer is problematic yet still struggle to locate the boundary between assistance, adaptation, and substitution. Ethical difficulty, therefore, may arise not only from an intention to violate rules but also from a normative vacuum that students resolve pragmatically.

The policy implication is that GenAI governance should not end with lists of applications or broad prohibitions. Moorhouse et al. (2023), Wang et al. (2024), Jin et al. (2025), and Tsao (2025) show that institutional guidance is always interpreted at the classroom level. The present study identifies the practical consequence: lecturer silence, task characteristics, and time pressure can become cues from which students infer acceptable boundaries. More operational guidance should be organized around task function and risk—for example, distinguishing AI use for explanation, feedback, outlining, technical correction, and final-answer production. The relevant principle is not merely whether AI is allowed, but how far it may contribute, which components must remain human-authored, what verification is required, and when AI use must be disclosed. This approach is consistent with Nartey (2024) and Williams (2023), who frame integrity in terms of responsibility, accuracy, and context.

For teacher education, these findings have a broader professional dimension. Pre-service teachers will become not only AI users but also instructional designers and rule-setters who determine acceptable AI use for their students. Dayagbil et al. (2025) and Kohnke et al. (2026) indicate that teacher readiness must encompass benefits, risks, privacy, ethics, and pedagogical strategy, while Prilop et al. (2025), Seufert et al. (2025), Aldemir et al. (2025), and Boos et al. (2026) connect AI literacy with pedagogical knowledge and responsible use. Related Indonesian work validating a TPCK-S instrument for hologram-based mathematics teaching also reflects the growing need to evaluate technology-pedagogy integration in teacher practice (Kaharuddin et al., 2025). The present study adds a further requirement: pre-service teachers must learn to set defensible limits on cognitive delegation. Authentic tasks should therefore require students to explain why AI was used, what was verified, what was independently revised, and why human contribution remained necessary. Professional competence is not demonstrated by obtaining an AI output; it is demonstrated by being able to justify the decision to use it.

Anxiety about AI detectors reveals another risk of governance that is overly detection-oriented. Some students altered their writing or used paraphrasing tools to reduce the likelihood of detection, shifting attention from argument quality toward strategies for avoiding a tool. This is consistent with Kofinas et al. (2025), suggesting that detection cannot serve as the sole response to integrity concerns in GenAI-mediated assessment. Lindkvist et al. (2026) demonstrate students' agency in restricting AI use when it conflicts with learning goals; similar agency should be cultivated among users through the ability to explain their rationale, human contribution, and verification process. Authentic assessment, transparent disclosure, and lecturer-student dialogue are therefore more educationally productive than reliance on detector scores alone.

Overall, the study offers two interconnected contributions. The Cognitive Partner, Practical Adaptor, and Passive Outsourcing typologies provide a framework for evaluating GenAI use through the distribution of cognitive responsibility, while implicit permission explains how unclear rules can encourage pragmatic ethical judgments. Together, they show that the central issue is not GenAI's presence, but the design of the relationship among task goals, AI contribution, verification, revision, and human accountability. The key implication is the need for risk-sensitive, task-explicit GenAI pedagogy and policy that preserve the intellectual and professional ownership of pre-service teachers.

5. Conclusion

This study shows that pre-service teachers use GenAI through three principal patterns: Cognitive Partner, Practical Adaptor, and Passive Outsourcing. The patterns differ less by frequency of use than by the level of verification, extent of independent revision, ownership of the final product, and degree of cognitive delegation. Most participants were Practical Adaptors, indicating that GenAI was primarily used to improve efficiency while retaining some human contribution. Passive Outsourcing, however, represents a condition in which technology begins to replace thinking processes that should form part of the learning experience.

Ethical dilemmas emerged most clearly when students did not receive explicit guidance. The perception of implicit permission shows that some students interpret the absence of a prohibition as legitimizing GenAI use. This finding indicates that learning guidelines should specify not only whether AI is permitted, but also which functions may be delegated, what forms of verification are required, and how students remain accountable for the outcome. In teacher education, this need has professional implications because patterns formed during preparation may shape how future teachers later guide their own students.

The study contributes by mapping a spectrum of cognitive delegation and identifying implicit permission as a mechanism that helps explain students' ethical decisions. Its limitations include a single study program, a relatively small participant group, and a design that was not intended to test causal relationships among themes. Future research should examine the typology across different disciplines, trace changes in GenAI-use patterns longitudinally, and develop instructional interventions that strengthen verification, self-regulation, and ethical decision-making among pre-service teachers.

6. Conflict of Interest

The authors declare no conflict of interest in the conduct or publication of this study.

7. Author Contributions

M.S.L.A. conceptualized the study, developed the instruments, led the data analysis, drafted the initial manuscript, managed interview data collection, conducted document analysis, and reviewed the literature. L.P.E.D. facilitated the focus-group discussions, supported data triangulation, reviewed the interpretations, and substantively edited the manuscript. All authors read and approved the final version of the manuscript. Contribution percentages: M.S.L.A. 60% and L.P.E.D. 40%.

8. Data Availability Statement

The data supporting the findings of this study are available from the corresponding author, M.S.L.A., upon reasonable request.

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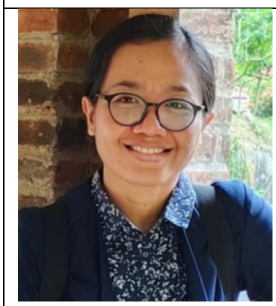

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