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Generative AI Adoption in Indonesian Higher Education: A Sociotechnical Analysis of Student Engagement, Digital and AI Literacy, and Academic Integrity

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Abstract

Generative artificial intelligence (GenAI) has rapidly entered higher education, changing how students access information and complete academic tasks. GenAI adoption cannot be understood as individual technology use alone, since it is also shaped by literacy, integrity, institutional rules, and pedagogical context. This study analyzes GenAI adoption in Indonesian higher education through a sociotechnical perspective, using a cross-sectional survey design analyzed with PLS-SEM, based on an Indonesian subset (N = 270) of a public global survey on students' early perceptions of ChatGPT. Students showed more favorable satisfaction and attitude scores than usage-frequency scores, indicating that positive perceptions did not automatically translate into intensive use. Structural modelling (N = 178) confirmed this: digital and AI literacy strongly predicted engagement (beta = 0.71, R2 = 0.51), whereas usage intensity did not. Digital and AI literacy is thus a key condition for responsible adoption, since students need to evaluate outputs, recognize limitations, and apply ethical judgment. Study-outcome and integrity blocks showed moderate-to-positive tendencies but continuing uncertainty about acceptable use. Responsible GenAI adoption in Indonesian higher education requires balanced institutional guidance, AI literacy development, assessment redesign, and clear academic integrity policies.

Keywords: Generative AI; ChatGPT; higher education; AI literacy; student engagement; academic integrity; sociotechnical analysis.

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1. Introduction

The rapid emergence of generative artificial intelligence (GenAI) has transformed higher education, as students and lecturers increasingly use tools such as ChatGPT for academic writing, idea generation, and independent learning. This shift affects how students access information and understand the boundaries of ethical practice. Prior work shows that large language models create opportunities for personalized learning, but also raise concerns about accuracy, misinformation, overdependence, and academic integrity (Kasneci et al., 2023; Lo, 2023; Rahman & Watanobe, 2023; Tlili et al., 2023).

GenAI adoption is best understood as part of a broader sociotechnical transformation involving students, lecturers, institutional policy, and academic culture, since technological change is shaped by the interaction between technical and social systems (Bostrom & Heinen, 1977; Baxter & Sommerville, 2011; Dwivedi et al., 2023). In Indonesia, AI regulation remains at an early, declarative stage (Solikhah, 2025), so universities must play a central role in filling this governance gap.

Technology acceptance theories help explain why students adopt GenAI: perceived usefulness and ease of use (Davis, 1989), performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al.,

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2003). These remain useful for individual acceptance, but adoption is also shaped by institutional support and ethical awareness, so they need to sit within a broader sociotechnical framework (Straub, 2009; Scherer et al., 2019).

GenAI adoption also bears on student engagement, the behavioral, emotional, and cognitive investment students bring to learning (Fredricks et al., 2004; Kahu, 2013). GenAI may help students clarify concepts and improve drafts, but may weaken engagement when used passively or as a substitute for critical thinking (Chan & Hu, 2023; Sullivan et al., 2023).

Digital and AI literacy are therefore central to responsible adoption, requiring students to evaluate information, identify bias, and understand what AI can and cannot do (Long & Magerko, 2020; Ng et al., 2021). Without sufficient literacy, students may accept AI-generated outputs uncritically (Laupichler et al., 2022; Celik, 2023; Shiri, 2024).

Academic integrity is among the most debated issues raised by GenAI, since its ability to produce fluent academic text blurs the line between legitimate support and misconduct (Cotton et al., 2023; Eke, 2023; Susnjak, 2022). Detection and prohibition alone are insufficient; universities need to redesign assessment and develop transparent guidelines for acceptable use (Crawford et al., 2023; Perkins et al., 2024; Kővári, 2024).

Prior research has examined GenAI's opportunities, AI literacy, and implications for assessment and scholarly ethics (Kasneci et al., 2023; Chan & Hu, 2023; Laupichler et al., 2022; Tlili et al., 2023; Lund et al., 2023), but these strands are typically treated separately, leaving a gap for an integrated sociotechnical framework spanning technology acceptance, literacy, engagement, and integrity, particularly relevant to Indonesian higher education.

Based on this gap, the study analyzes GenAI adoption in Indonesian higher education from a sociotechnical perspective, examining the relationships between sociotechnical factors, digital and AI literacy, GenAI adoption, student engagement, and academic integrity, integrating technology-adoption theory, sociotechnical systems theory, engagement literature, AI literacy, and academic-integrity perspectives.

This study contributes theoretically by positioning GenAI adoption within a sociotechnical framework rather than treating it solely as individual technology acceptance; empirically by focusing on Indonesian higher education as a developing-country context; and practically by informing universities, lecturers, and policymakers on AI literacy programs, ethical guidelines, and assessment strategies that support innovation while maintaining academic integrity.

2. Literature Review

2.1. Sociotechnical Perspective on Generative AI Adoption in Higher Education

GenAI adoption in higher education should be understood as a sociotechnical phenomenon rather than merely the use of a digital tool, since technical and social systems are interdependent (Bostrom & Heinen, 1977; Baxter & Sommerville, 2011). Tools such as ChatGPT, Gemini, and Copilot increasingly support academic writing and independent learning, but also affect assessment and institutional governance, so adoption must be examined through the interaction of technological affordances, student behavior, and institutional policy.

This relevance follows from the fact that GenAI creates opportunities and risks simultaneously, supporting understanding of difficult concepts while raising concerns about misinformation, overdependence, and assessment validity (Kasneci et al., 2023; Lo, 2023; Tlili et al., 2023). This study therefore positions GenAI adoption within a sociotechnical framework spanning technology acceptance, digital and AI literacy, institutional support, student engagement, and academic integrity (Dwivedi et al., 2023; Nguyen et al., 2023).

2.2. Technology Acceptance and Generative AI Adoption

Technology acceptance theory helps explain how students respond to new digital tools. The Technology Acceptance Model holds that perceived usefulness and ease of use shape acceptance (Davis, 1989), while UTAUT adds performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), both widely used in educational-technology research.

Technology acceptance theory helps explain how students respond to GenAI: perceived usefulness and ease of use shape acceptance (Davis, 1989), while UTAUT adds performance expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). GenAI differs from earlier educational technologies because it can generate text and reasoning outright, so TAM and UTAUT need to sit within a broader sociotechnical analysis of institutional and literacy-related factors (Straub, 2009; Scherer et al., 2019). Students generally perceive GenAI as useful, but also express concerns about reliability and integrity (Chan & Hu, 2023; Strzelecki, 2023).

2.3. Digital and AI Literacy

Digital literacy in higher education extends beyond operating platforms to evaluating information and using digital tools responsibly. GenAI adoption further requires AI literacy: understanding basic AI concepts, evaluating outputs, recognizing bias and limitations, and using AI ethically (Long & Magerko, 2020; Ng et al., 2021), competencies that matter because GenAI outputs often appear fluent even when inaccurate.

AI literacy is not only a technical skill but also a critical and ethical competence (Laupichler et al., 2022; Celik, 2023; Shiri, 2024). Students with stronger literacy are more likely to use GenAI critically and treat it as a learning assistant, whereas students with limited literacy may accept AI output uncritically, making digital and AI literacy central to connecting technological use with academic judgment and ethical responsibility. These foundations are increasingly cultivated well before university entry, as digital literacy initiatives now extend into early childhood education through structured, curated media rather than unsupervised internet use (Rahayu et al., 2023), suggesting that incoming higher-education students arrive with variable baseline familiarity with digital tools that AI-literacy instruction must build upon rather than assume.

2.4. Generative AI and Student Engagement

Student engagement, a multidimensional construct spanning behavioral, emotional, and cognitive participation in learning (Fredricks et al., 2004; Kahu, 2013), can be strengthened by technologies that provide timely feedback and support active learning (Henrie et al., 2015; Bond et al., 2020). GenAI has the potential to deepen engagement by helping students clarify concepts, generate examples, and explore alternative explanations.

This relationship is not always positive: engagement may weaken when students use GenAI passively or substitute automated responses for their own critical thinking (Chan & Hu, 2023; Sullivan et al., 2023; Kasneci et al., 2023; Tlili et al., 2023). From a sociotechnical view, GenAI-supported engagement depends on the interaction between student motivation, literacy, lecturer guidance, and institutional policy.

2.5. Generative AI and Academic Integrity

Academic integrity, honesty, trust, fairness, and ethical conduct in academic work, protects the credibility of learning and assessment. GenAI complicates this because students can generate essays, summaries, and code with minimal effort, creating new challenges for plagiarism detection, authorship attribution, and assessment validity.

Cotton et al. (2023) argue that ChatGPT-generated text can be difficult to distinguish from student-written work, Eke (2023) and Susnjak (2022) similarly highlight integrity risks. Detection tools alone are limited, however, since AI-generated text can be edited or paraphrased; scholars instead recommend redesigning assessment and developing clear AI-use policies (Crawford et al., 2023; Perkins et al., 2024; Kővári, 2024).

Academic integrity is closely tied to digital and AI literacy: students who understand GenAI's limitations are more likely to use it for brainstorming rather than as a substitute for original analysis. A sociotechnical view frames integrity as shaped by technology design, assessment systems, institutional policy, and student literacy, not as a purely individual moral issue. This framing also connects academic integrity to broader character-education efforts that instill honesty as a core value from early schooling onward (Aini, 2023), implying that university-level responses to GenAI-related integrity risks build on, but cannot rely solely on, values students are expected to bring from earlier stages of education.

2.6. Institutional Support and Academic Governance

Institutional support, facilitating conditions in technology-acceptance terms (Venkatesh et al., 2003), includes digital infrastructure, AI-use guidelines, lecturer training, literacy programs, and integrity regulations. This role is especially important in Indonesia, where data-protection law has not yet established technical standards or oversight mechanisms for AI-based educational platforms, leaving universities largely dependent on their own governance to safeguard student data and regulate responsible use (Mu'min et al., 2026; Solikhah, 2025). This gap is not confined to education: Indonesia's broader digital economy shows similarly fragmented and reactive oversight, with legal responsibility for platform-based risks to users remaining unclear across sectors (Siregar et al., 2025), and normative tension between repressive and restorative regulatory paradigms persisting even where digital conduct involving minors is concerned (Ginting et al., 2026), underscoring that Indonesian AI governance in higher education is one instance of a wider pattern of regulatory lag behind digital innovation.

Rapid GenAI adoption has created uncertainty across institutions, with students receiving inconsistent messages from different lecturers. Institutional support can transform GenAI into a responsible learning resource by providing clear guidelines, integrating AI literacy into curricula, and encouraging transparent disclosure, connecting GenAI's technical availability with the social and ethical conditions of its use.

2.7. Conceptual Framework

Based on the literature, this study conceptualizes GenAI adoption in Indonesian higher education as a sociotechnical process shaped by technological, individual, institutional, and ethical dimensions. Technology-acceptance factors capture how students perceive GenAI's usefulness and relevance; digital and AI literacy reflects students' capacity to evaluate outputs critically; and institutional support represents the role of universities and assessment policy in shaping appropriate use.

Within this framework, GenAI adoption is a practice embedded in academic norms and institutional governance, with student engagement and academic integrity as key educational implications. This framework is specified as a structural model and tested empirically, drawing on technology-acceptance theory, AI-literacy scholarship, and the sociotechnical perspective. The following hypotheses are proposed, where PE denotes perceived capability, SAT satisfaction and attitude, AILIT digital and AI literacy, USE GenAI adoption, ENG student engagement, INT academic-integrity concern, and REG regulation endorsement:

H1. Perceived capability (PE) positively influences satisfaction and attitude (SAT) toward ChatGPT.

H2. Satisfaction and attitude (SAT) positively influence GenAI adoption (USE).

H3. Perceived capability (PE) positively influences GenAI adoption (USE).

H4. Digital and AI literacy (AILIT) positively influences GenAI adoption (USE).

H5. Digital and AI literacy (AILIT) positively influences student engagement (ENG).

H6. GenAI adoption (USE) positively influences student engagement (ENG).

H7. GenAI adoption (USE) is associated with academic-integrity concern (INT).

H8. Digital and AI literacy (AILIT) is associated with academic-integrity concern (INT).

H9. Regulation endorsement (REG) is associated with academic-integrity concern (INT).

3. Research Method and Materials

3.1. Research Design

This study employed an explanatory cross-sectional survey design, analyzed through partial least squares structural equation modeling (PLS-SEM), grounded in a sociotechnical perspective. This design was chosen because GenAI adoption involves the interaction between technological affordances, student practices, literacy, academic norms, institutional support, and ethics, consistent with sociotechnical systems theory (Bostrom & Heinen, 1977; Baxter & Sommerville, 2011). The analytical workflow is shown in Figure 1.

As shown in Figure 1, the research design comprised five stages: public dataset identification of sources relevant to GenAI, ChatGPT, and academic governance; dataset screening for relevance and suitability; dataset classification into quantitative survey data and qualitative or policy data; data processing and harmonization via descriptive analysis and thematic coding; and sociotechnical interpretation integrating the harmonized findings.

3.2. Data Sources and Materials

This study used publicly available secondary data. The primary empirical material was the Indonesian higher education subset extracted from the Higher Education Students' Early Perceptions of ChatGPT: Global Survey Data (Ravselj et al., 2025a), limited to respondents affiliated with higher education institutions located in Indonesia.

The Indonesian subset was defined by filtering the original dataset by institutional location, yielding 270 respondents, with structured survey responses coded from Q1 to Q40 across several multi-item blocks. The full global dataset was retained only as a contextual reference rather than the primary object of analysis.

In addition to the survey subset, the study drew on supporting documentary materials, Indonesian higher education guidelines, academic-integrity statements, and AI-literacy resources, because GenAI adoption in higher education is shaped by institutional and ethical context as well as individual technology use. These materials were used to interpret institutional support, academic governance, and responsible-use expectations.

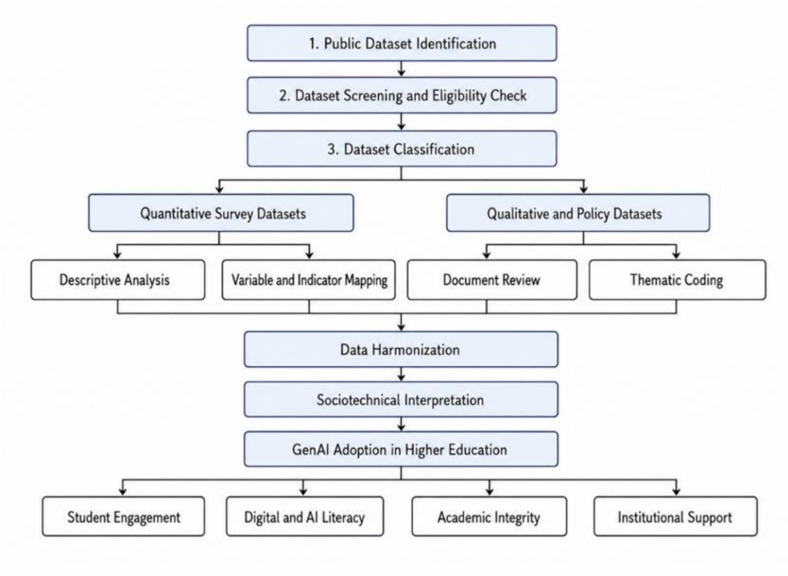

Figure 1. Analytical Workflow of the Study

Table 1. Data sources and research materials

Code	Data Source / Material	Type	Scope	Use in This Study
D1-ID	Indonesian higher education subset of *Higher Education Students' Early Perceptions of ChatGPT: Global Survey Data*	Public survey dataset	Respondents affiliated with higher education institutions located in Indonesia	Primary empirical data for analyzing GenAI adoption, student perceptions, digital and AI literacy indicators, engagement-related outcomes, and ethical concerns in Indonesian higher education
D1-G	Full global survey dataset	Public survey dataset	Higher education students from multiple countries and territories	Source dataset and contextual reference for positioning Indonesian findings within broader international patterns
D2-ID	Indonesian higher education guidelines or institutional documents related to GenAI use	Documentary materials	Indonesian higher education context	Supporting material for interpreting institutional support, academic governance, and responsible GenAI use
D3-ID	Academic integrity and assessment-related documents	Documentary materials	Higher education policy and academic practice context	Supporting material for analyzing ethical boundaries, originality expectations, disclosure practices, and assessment-related implications
D4-ID	AI literacy and responsible AI-use resources	Educational and guidance materials	Higher education and digital literacy context	Supporting material for interpreting digital and AI literacy as conditions for responsible GenAI adoption

Before analysis, the Indonesian subset was checked for missing values, incomplete responses, and inconsistent institutional information, with item-level valid responses reported where completeness varied across items.

Because the survey and documentary materials differed in format and purpose, they were not merged into a single dataset: the survey was analyzed descriptively while the documentary materials were reviewed thematically, and the two were integrated during interpretation to combine student-level evidence with institutional-level context.

3.3. Dataset Structure

The dataset structure comprised two layers: the Indonesian higher education survey subset and supporting documentary materials, capturing both student-level perceptions and the institutional context of GenAI adoption.

The first layer was the Indonesian subset extracted by institutional location from the global dataset (Ravselj et al., 2025a), structured using coded items Q1 to Q40 across multi-item blocks, interpreted through the dataset documentation rather than column labels alone. The second layer comprised publicly accessible Indonesian higher education guidelines and AI-literacy resources, used as contextual sources to interpret institutional support and responsible-use expectations. Table 2 summarizes the dataset structure.

Table 2. Dataset Structure and Analytical Use

Data Layer	Source Code	Data Type	Main Information	Analytical Use
Indonesian higher education survey subset	D1-ID	Student-level quantitative survey data	Respondent background, institutional affiliation, ChatGPT use, perceptions, attitudes, ethical concerns, study-related outcomes, skills development, and related survey items	To describe student-level patterns of GenAI adoption, digital and AI literacy indicators, engagement-related outcomes, and academic integrity concerns in Indonesian higher education
Global survey dataset	D1-G	Public global survey dataset	Full international dataset from which the Indonesian subset was extracted	To provide contextual reference for positioning Indonesian findings within broader international patterns
Institutional policy materials	D2-ID	Documentary materials	Indonesian higher education guidelines, AI-use policies, lecturer guidance, and responsible-use recommendations	To interpret institutional support, academic governance, and policy framing of GenAI use
Academic integrity materials	D3-ID	Institutional and assessment documents	Academic integrity statements, plagiarism rules, originality expectations, disclosure expectations, and assessment-related documents	To analyze ethical boundaries, originality expectations, and academic integrity implications of GenAI use
AI literacy and responsible-use materials	D4-ID	Educational and guidance resources	AI literacy guidance, responsible-use principles, student support resources, and lecturer-facing recommendations	To interpret digital and AI literacy as enabling conditions for responsible GenAI adoption

The survey subset was used to identify adoption patterns: items on use, attitude, and skills development described how students engage with ChatGPT, while regulation and ethical-concern items supported the analysis of integrity and responsible use; demographic items described the respondent background.

Policy, integrity, and AI-literacy materials were reviewed thematically for institutional support, governance, and ethical themes, helping contextualize the survey findings within the broader Indonesian higher-education environment. This dual approach preserved the integrity of each source while allowing them to be integrated during interpretation.

3.4. Analytical Dimensions

The analysis was guided by sociotechnical analytical dimensions aligned with the dataset and supporting materials, operationalized as reflective latent constructs examined through a structural model: technology acceptance, GenAI adoption, digital and AI literacy, student engagement, academic integrity, and institutional support.

Technology acceptance captured students' perceptions of GenAI's usefulness (Davis, 1989; Venkatesh et al., 2003, 2012); GenAI adoption captured reported use of ChatGPT; digital and AI literacy captured students' ability to evaluate outputs critically (Long & Magerko, 2020; Ng et al., 2021); engagement captured behavioral, emotional, and cognitive involvement (Fredricks et al., 2004; Kahu, 2013); integrity captured concerns about originality and disclosure (Cotton et al., 2023); and institutional support captured guidelines and governance (Bostrom & Heinen, 1977). Table 3 summarizes these dimensions.

Table 3. Analytical Dimensions and Indicators

Analytical Dimension	Operational Focus	Related Data Sources	Analytical Use
Technology acceptance	Perceived usefulness, perceived ease of use, relevance of GenAI tools, and students' attitudes toward ChatGPT	D1-ID, D1-G	To interpret students' acceptance of GenAI tools in academic activities
GenAI adoption	Reported use of ChatGPT, academic use purposes, learning support, task assistance, and frequency or pattern of use	D1-ID	To describe how students use GenAI in Indonesian higher education contexts
Digital and AI literacy	Ability to evaluate AI-generated outputs, awareness of AI limitations, responsible use, and skill development	D1-ID, D4-ID	To examine students' readiness to use GenAI critically and responsibly
Student engagement	Study support, learning motivation, academic participation, understanding of course materials, and perceived learning outcomes	D1-ID	To interpret how GenAI use relates to students' learning engagement
Academic integrity	Ethical concerns, originality, authorship, disclosure, plagiarism risk, and acceptable boundaries of AI assistance	D1-ID, D3-ID	To analyze integrity-related concerns and ethical implications of GenAI use
Institutional support	University guidelines, lecturer guidance, assessment policy, AI-use rules, and academic governance	D2-ID, D3-ID, D4-ID	To interpret how institutional context shapes responsible GenAI adoption

Survey items were mapped into these dimensions based on the dataset documentation, questionnaire structure, and conceptual relevance, with each reflective latent construct linked to its questionnaire indicators as summarized in Table 4.

Table 4. Construct Operationalization (Reflective Measurement Model)

Construct	Reflective indicators (questionnaire items)	Theoretical anchor
PE	Q19d, Q19e, Q19f, Q19g	Performance expectancy / perceived capability (Davis, 1989; Venkatesh et al., 2003)
SAT	Q24e, Q24f, Q24g, Q25b, Q25c, Q25d	Satisfaction and attitude (Davis, 1989; Venkatesh et al., 2012)
AILIT	Q28h, Q28i, Q29d, Q29e, Q29i	Digital and AI literacy (Long & Magerko, 2020; Ng et al., 2021)
USE	Q15, Q18a, Q18i, Q18k	GenAI adoption / use behaviour (Venkatesh et al., 2003, 2012)
ENG	Q26e, Q26f, Q26h, Q27e, Q27h	Student engagement and study outcomes (Fredricks et al., 2004; Kahu, 2013)
INT	Q22b, Q22c, Q22d, Q22j	Academic-integrity concern (Cotton et al., 2023; Eke, 2023)
REG	Q21a, Q21b, Q21c, Q21d	Regulation and ethical norms (Venkatesh et al., 2003)

Supporting documentary materials were mapped onto the same dimensions, institutional guidelines informed institutional support and integrity, while AI-literacy resources strengthened the interpretation of digital and AI literacy, enabling the study to integrate quantitative survey patterns with documentary evidence within a coherent sociotechnical framework.

3.5. Data Processing and Analysis

Data processing followed several stages: subset filtering, data screening, variable mapping, descriptive analysis, documentary review, and integrated interpretation, designed to keep the analysis consistent with the Indonesian higher-education focus and the dataset structure.

Subset filtering screened the global dataset for respondents affiliated with higher education institutions located in Indonesia, using institutional location as the inclusion criterion, yielding 270 respondents; the global dataset was retained only as a contextual reference (Ravselj et al., 2025a, 2025b).

Variable and indicator mapping aligned the coded Q1-Q40 items with the study's analytical dimensions (Ravselj et al., 2025a, 2025b). Descriptive analysis then summarized frequency distributions across usage, literacy, engagement, and integrity items, informed by the relevant theoretical literature (Davis, 1989; Long & Magerko, 2020; Fredricks et al., 2004; Cotton et al., 2023).

Publicly available information on institutional AI guidance and integrity expectations was consulted only as background for interpreting the survey findings and was not treated as a separate coded data source; all empirical claims rest on the survey data.

Findings from the descriptive analysis and documentary review were integrated in a final sociotechnical interpretation stage. The analytical constructs were also tested inferentially using PLS-SEM: the measurement model was assessed for reliability and validity, common method bias was evaluated via Harman's test and full-collinearity VIFs, and the structural model was estimated with 500 bootstrap resamples, benchmarked against the global sample using Mann-Whitney U tests. Table 5 summarizes this procedure.

Table 5. Data Processing and Analysis Procedure

Stage	Procedure	Purpose	Output
Subset filtering	Selecting respondents affiliated with higher education institutions located in Indonesia	To align the dataset with the Indonesian higher education focus	Indonesian higher education subset with 270 respondents
Data screening and cleaning	Checking missing values, incomplete responses, institutional consistency, and item-level response completeness	To ensure data quality and analytical suitability	Cleaned analytical dataset with item-level valid responses
Variable and indicator mapping	Mapping coded questionnaire items into analytical dimensions	To connect dataset variables with the conceptual and analytical framework	Analytical item map
Descriptive analysis	Summarizing frequency distributions, response tendencies, and central patterns	To identify student-level patterns of GenAI adoption and related dimensions	Descriptive findings
Documentary review	Reviewing policy, academic integrity, assessment, and AI literacy materials thematically	To interpret institutional, ethical, and literacy-related context	Thematic contextual evidence
Integrated interpretation	Combining survey findings and documentary evidence	To explain GenAI adoption as a sociotechnical phenomenon in Indonesian higher education	Integrated interpretation of GenAI adoption

3.6. Formalized Subset Construction and Data Pipeline

To ensure technical precision and reproducibility, the Indonesian subset was extracted from the global dataset through a deterministic pipeline filtering respondents by institutional location and usage readiness, detailed in the following steps:

- **Step 1:** Define the initial country base: $D_{cit} = \{r\text{:Respondent Country} = \text{Indonesia}\}$ (Total: 281 records)
- **Step 2:** Apply institutional location filter: $D_{HE} = \{r \in D_{cit}\text{:Institutional Location} = \text{Indonesia}\}$ (Retained: 270)

- **Step 3:** Exclusion criteria: Remove r if the institution is non-Indonesian or if critical missing values are present (11 excluded).
- **Step 4:** Standardize institution strings into grouped categories for profiling.
- **Step 5:** Gate users: Retain respondents who proceeded to the usage-related items ($Q13 = 1$), yielding 204 users.
- **Step 6:** Final listwise-complete subset for PLS-SEM inferential modeling yielded $N = 178$.

3.7. Research Validity and Ethical Considerations

Research validity was strengthened through transparent data selection, systematic subset filtering, variable mapping, and integration of survey data with supporting documentary materials, yielding a final Indonesian subset of 270 respondents after institutional-location filtering.

Because the dataset used coded questionnaire labels (Q1-Q40), each item was interpreted through the dataset documentation and the associated global study (Ravselj et al., 2025a, 2025b) rather than column names alone. Validity was further supported through triangulation: survey data identified student-level response patterns while documentary materials provided institutional and ethical context.

The analytical dimensions drew on established literature: technology acceptance (Davis, 1989; Venkatesh et al., 2003, 2012), digital and AI literacy (Long & Magerko, 2020; Ng et al., 2021; Laupichler et al., 2022), student engagement (Fredricks et al., 2004; Kahu, 2013; Bond et al., 2020), and academic integrity (Cotton et al., 2023; Eke, 2023; Sullivan et al., 2023).

Ethically, this study used only publicly available secondary data at the aggregate level, without direct interaction with respondents; institutional information was used solely to define the Indonesian subset and contextualize findings. GenAI use was treated as a sociotechnical practice that can support learning when guided by adequate literacy and institutional governance, while recognizing its risks for academic integrity when used to bypass learning.

Several limitations were acknowledged: the study relied on secondary data with variables determined by the original dataset creators; the Indonesian subset, extracted from a global dataset, may not represent all Indonesian higher-education institutions; the valid number of responses varies across items due to missing values; and the documentary materials served as contextual rather than statistically comparable evidence.

4. Results and Discussion

4.1. Indonesian Higher Education Subset and Data Readiness

The first stage of analysis prepared the Indonesian subset for descriptive and interpretive analysis. The working file contained 281 records associated with Indonesia in the respondent-country field and 174 variables spanning demographic, institutional, and ChatGPT-related fields; institutional location was used as the main inclusion criterion for the final analytical subset.

This criterion was needed because respondent-country identity alone did not represent the Indonesian higher-education context, some records were linked to institutions located outside Indonesia or had missing institutional-location data, so the study retained only respondents affiliated with higher education institutions located in Indonesia, ensuring the sample reflected the Indonesian higher-education environment. The filtering process is summarized in Table 6 and Figure 2.

Table 6. Indonesian Higher Education Subset Filtering

Filtering Category	Description	Number of Records
Initial working file	Records associated with Indonesia in the respondent-country field	281
Retained records	Respondents affiliated with higher education institutions located in Indonesia	270
Excluded records	Records linked to non-Indonesian or missing institutional locations	11
Final analytical subset	Indonesian higher education subset used for descriptive analysis	270

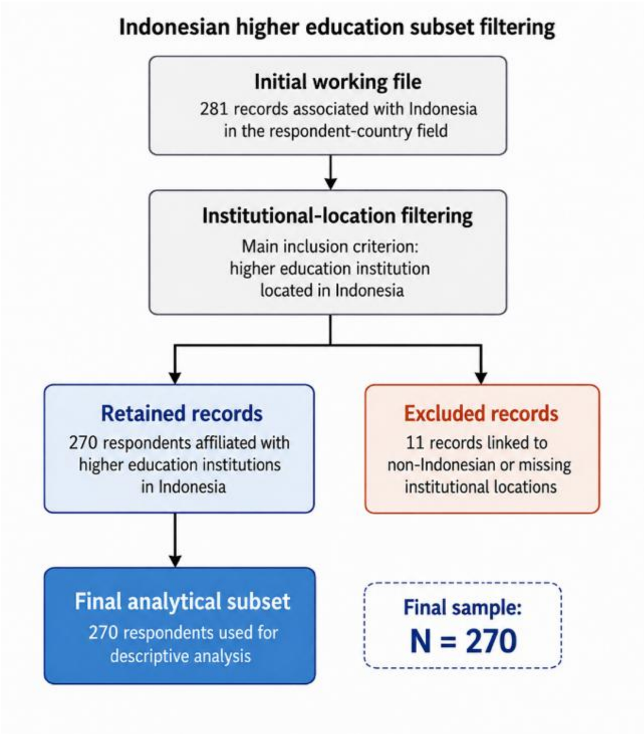

Figure 2. Indonesian Higher Education Subset Filtering

As shown in Table 6 and Figure 2, institutional-location filtering produced a final analytical subset of 270 respondents, with 11 records excluded for non-Indonesian or missing institutional locations.

Using institutional location as the filtering criterion strengthened contextual validity, since GenAI adoption is shaped by institutional rules and assessment systems, not just individual characteristics. The dataset's coded Q1-Q40 structure supported multidimensional analysis across technology acceptance, literacy, engagement, integrity, and institutional support (Ravselj et al., 2025a, 2025b).

Item-level completeness was also examined, since some records contained missing responses; the analysis therefore reports valid responses per item rather than assuming uniform completeness across the 270-respondent subset. The availability of an Indonesian subset within a larger global survey provides empirical evidence for examining GenAI adoption within Indonesia's higher-education environment.

Overall, the dataset preparation produced a clearly defined analytical subset of 270 respondents suitable for descriptive and structural analysis.

4.2. Respondent and Institutional Profile

The next stage examined the respondent and institutional profile of the 270-respondent subset. The institutional-affiliation field, recorded as open text, contained spelling, language, and naming variations that were standardized into broader institution groups for reporting, summarized in Table 7.

Table 7. Institutional Profile of the Indonesian Higher Education Subset

Institution Group	Number of Respondents	Percentage
Bina Nusantara University / BINUS variants	111	41.1%
Poltekkes Kemenkes Banjarmasin / health polytechnic variants	80	29.6%
Muhammadiyah University of Metro variants	74	27.4%
Missing or blank institutional entry	3	1.1%
Other or unclear open-text entry	2	0.7%
Total	**270**	**100.0%**

Table 7 shows the subset concentrated in three institutional groups: Bina Nusantara University/BINUS variants (111 respondents, 41.1%), Poltekkes Kemenkes Banjarmasin and related health-polytechnic variants (80, 29.6%), and

Muhammadiyah University of Metro variants (74, 27.4%), with only a small share of missing or unclear entries. The age profile is summarized in Table 8.

Table 8. Age Profile of the Indonesian Higher Education Subset

Age Category	Number of Respondents	Percentage of Valid Age Responses
17 years	1	0.4%
18 years	120	45.8%
19 years	67	25.6%
20 years	40	15.3%
21 years	20	7.6%
22 years and above	14	5.3%
Valid age responses	**262**	**100.0%**
Missing or year-like entries requiring cleaning	8	—
Final analytical subset	**270**	—

Table 8 shows the profile dominated by students aged 18-20 years, accounting for 227 of 262 valid age responses (86.6%), with 18-year-olds the largest single category (120 respondents, 45.8%). Eight entries were missing or year-like and excluded from the valid-age percentage. The respondent and institutional profile is visualized in Figure 3.

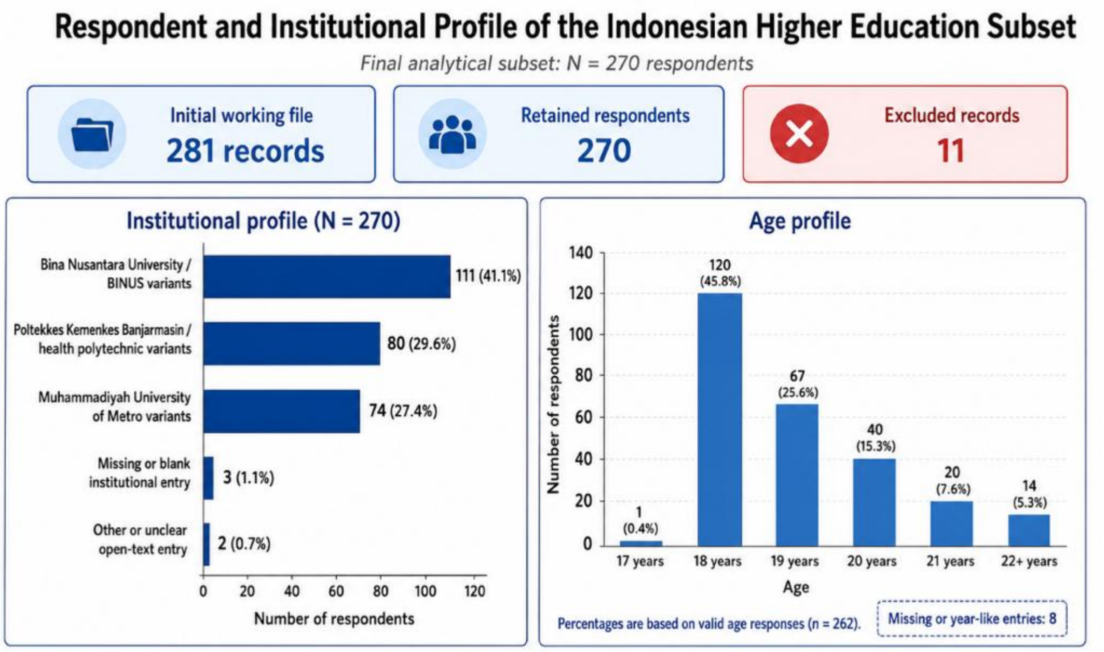

Figure 3. Respondent and Institutional Profile of the Indonesian Higher Education Subset

Figure 3 shows that 270 of 281 initial records were retained after institutional-location filtering, concentrated in three major institution groups, with most valid age responses between 18 and 20 years. The sample should not be read as nationally representative of Indonesian higher education.

4.3. GenAI Adoption and Technology Acceptance

This section presents the descriptive findings related to GenAI adoption and technology acceptance among respondents in the Indonesian higher education subset. The analysis focused on three main indicators: the initial ChatGPT-use gate item, the usage frequency block, and the satisfaction and attitude block. In the original survey structure, the usage-related questions were covered in the early usage block, while the satisfaction and attitude items were represented in subsequent evaluative item blocks (Ravšelj et al., 2025a; Ravšelj et al., 2025b). Because item-level responses contained missing values, the analysis reports valid responses for each block rather than assuming that all 270 respondents answered every item. The descriptive results are summarized in Figure 4.

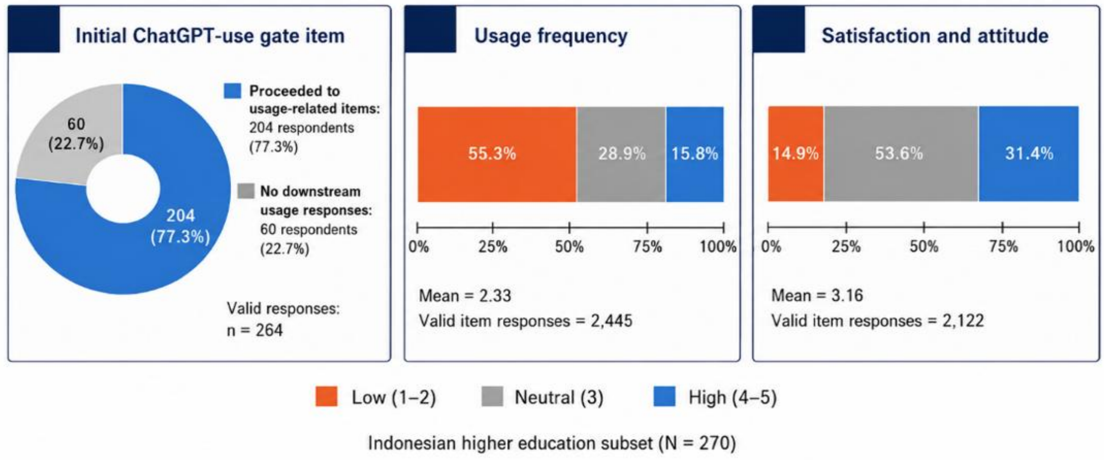

Figure 4. Genai Adoption and Technology Acceptance among The Indonesian Higher Education Subset

As shown in Figure 4, the initial ChatGPT-use gate item produced 264 valid responses; 204 (77.3%) proceeded to the usage-related items, while 60 (22.7%) did not, indicating that most valid respondents had sufficient prior exposure to ChatGPT to continue into the usage section.

The usage-frequency block showed relatively low intensity: across 2,445 valid item responses, the mean score was 2.33, with 55.3% in lower categories, 28.9% neutral, and only 15.8% in higher categories, suggesting ChatGPT had entered students' academic experience without yet becoming a routine, intensive practice.

A different pattern emerged for satisfaction and attitude: across 2,122 valid item responses, the mean score was 3.16, with only 14.9% in lower categories, 53.6% neutral, and 31.4% in higher categories, a more moderate-to-positive attitude than usage frequency alone would suggest.

This contrast between low usage intensity and more favorable attitudes matters for interpreting GenAI adoption: positive attitudes do not always translate into intensive use, since perceived usefulness and ease of use may support favorable perceptions while actual usage remains limited by academic uncertainty or incomplete integration into learning routines (Davis, 1989; Venkatesh et al., 2003, 2012).

This is consistent with broader findings that ChatGPT is adopted for explanation and task assistance to varying degrees across contexts (Kasneci et al., 2023; Lo, 2023; Tlili et al., 2023); the Indonesian subset reflects a transitional stage of exposure without full embedding into everyday academic practice, consistent with Rogers' (2003) diffusion-of-innovation view.

From a sociotechnical view, a positive attitude toward GenAI does not automatically ensure frequent, critical, or responsible use, since actual use is also shaped by digital and AI literacy, integrity concerns, lecturer expectations, and institutional rules, supporting the argument that GenAI adoption should be understood as a practice shaped by broader academic and institutional conditions, not just individual acceptance.

Overall, GenAI adoption was already evident but not yet intensive, with more favorable attitudes than usage frequency alone would imply, highlighting the importance of institutional support, digital and AI literacy, and clear academic guidance in helping students move toward more meaningful, responsible GenAI use.

4.4. Digital and AI Literacy in GenAI Use

The previous section's contrast between favorable attitudes and lower usage frequency matters for digital and AI literacy, since favorable attitudes do not automatically indicate that students can evaluate, verify, and use AI-generated outputs responsibly.

This study interprets digital and AI literacy as the critical condition connecting students' perceptions of ChatGPT with responsible academic use, guided by the dataset documentation given the coded questionnaire variables, focusing on skills such as evaluating generated content, recognizing limitations, verifying information, and applying ethical judgment. This relationship is illustrated in Figure 5.

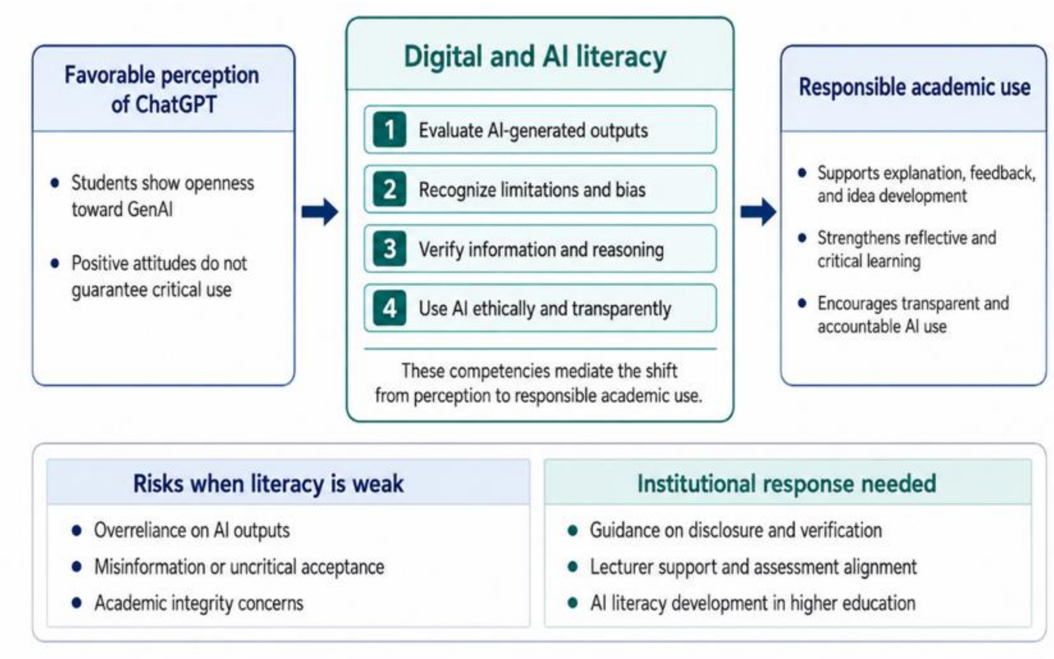

Figure 5. Digital and AI Literacy in Responsible GenAI Use

Figure 5 shows that digital and AI literacy functions as a key condition between students' favorable perceptions of ChatGPT and responsible academic use: perceptions of usefulness need to be matched by the ability to assess the reliability and limitations of AI-generated responses, since without such literacy students may use GenAI passively or uncritically, increasing risks of misinformation, dependency, and integrity problems.

This aligns with AI-literacy scholarship emphasizing that learners need more than operational skill: Long and Magerko (2020) define AI literacy as the competencies to critically evaluate and collaborate with AI systems, and Ng et al. (2021) add the knowledge, skills, and attitudes needed to use AI responsibly, suggesting Indonesian students need not only familiarity with ChatGPT but the capacity to question and validate its outputs.

The moderate-to-positive attitude pattern may signal openness to GenAI-supported learning, but openness alone is not sufficient, since fluent AI-generated text does not guarantee accuracy or originality (Van Dis et al., 2023; Liebrenz et al., 2023).

AI-mediated learning requires students to evaluate machine-generated outputs whose sources are not always transparent, demanding critical understanding and ethical awareness (Shiri, 2024). This is meaningful only when embedded in reflective practices (Mah & Grohbiel, 2024; Tzirides et al., 2023), and requires institutional support, since universities need to clarify how GenAI may be used and when disclosure is required (Celik, 2023).

The Indonesian subset therefore suggests GenAI adoption is a literacy-dependent process, linked to the broader institutional digital transformation of AI in higher education (Zawacki-Richter et al., 2019; Chen et al., 2020). Positive attitudes create opportunities for learning support realized only when students use AI critically, making AI-literacy development a strategic priority. This attitude-practice disconnect echoes a recurring pattern in other Indonesian professional and economic domains, where a persistent "competency gap" separates theoretical readiness from practice-ready skill, as documented among law students transitioning from doctrinal study to courtroom practice (Khaerunnisa et al., 2026), and where the benefits of digital adoption more broadly are similarly mediated by literacy, capital access, and social support rather than by technology availability alone (Nendi, 2025).

4.5. Student Engagement and Study-Related Outcomes

This section examines student engagement via the study-related outcome blocks (Q26, Q27), reported as valid item responses per block. Results are summarized in Figure 6.

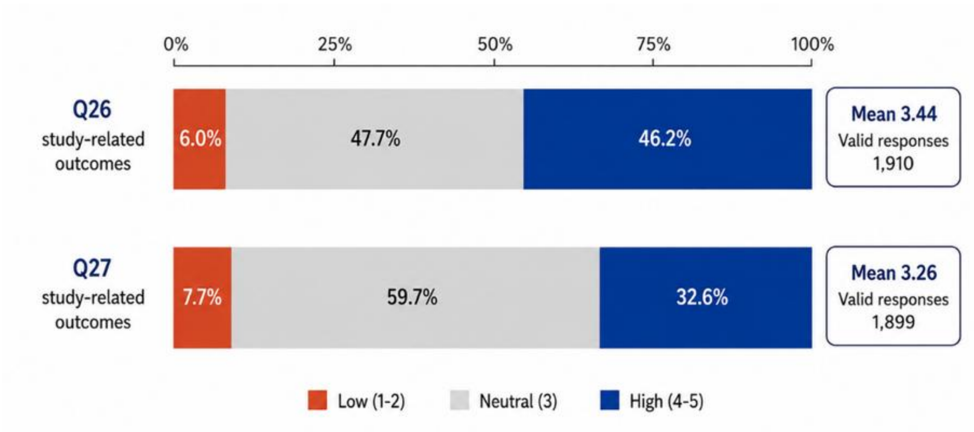

Figure 6. Study-Related Outcomes and Student Engagement Indicators

As shown in Figure 6, the Q26 block showed a moderate-to-positive tendency: across 1,910 valid item responses, the mean score was 3.44, with 6.0% low, 47.7% neutral, and 46.2% high responses, suggesting many respondents saw ChatGPT as meaningfully supporting study-related outcomes, though nearly half remained neutral.

The Q27 block showed a slightly lower but still moderate tendency: across 1,899 valid item responses, the mean score was 3.26, with 7.7% low, 59.7% neutral, and 32.6% high responses, a larger neutral share and smaller high share than Q26, indicating uneven perceptions of ChatGPT's contribution to study-related outcomes.

These findings suggest ChatGPT is perceived as useful for some study-related purposes, but its contribution to engagement remains conditional and uneven (Fredricks et al., 2004; Kahu, 2013; Henrie et al., 2015; Bond et al., 2020). ChatGPT's educational value depends on the interaction between students, AI literacy, and institutional guidance: used to compare ideas it may strengthen cognitive engagement, but relied on without verification it may reduce deeper learning and raise integrity risks (Crawford et al., 2023; Perkins et al., 2024).

Overall, GenAI adoption may support engagement and study-related outcomes conditionally, contributing to explanation, feedback, and efficiency when used critically and with institutional guidance, but remaining superficial without pedagogical direction and literacy development.

4.6. Academic Integrity and Responsible GenAI Use

This section examines academic integrity and responsible GenAI use based on the regulation and ethical-concern blocks (Q20-Q23) (Ravselj et al., 2025b), reporting valid item responses per block.

Results show moderate concern and awareness: across Q21-Q23, 3,466 valid item responses averaged 3.18, with 16.9% low, 50.9% neutral, and 32.2% high responses, indicating that academic integrity and responsible use were recognized by many respondents, though the dominant neutral response suggests ethical understanding and regulatory certainty were not yet fully established.

At the block level, Q21 showed the strongest agreement (mean 3.33, 35.3% high) and Q23 a similar moderate-to-positive pattern (mean 3.30, 34.6% high), while Q22 was more divided (mean 3.08, 24.4% low), suggesting students recognize the importance of responsible use but remain uncertain about the boundary between acceptable assistance and misconduct.

These findings matter because GenAI challenges assumptions about authorship and assessment, since ChatGPT can generate fluent text difficult to distinguish from student work (Cotton et al., 2023; Eke, 2023), and the high neutral-response share suggests integrity guidance should be clearer, framed not only as cheating prevention but as guidance on acceptable assistance, disclosure, and verification (Sullivan et al., 2023; Perkins et al., 2024).

Overall, academic integrity is central to GenAI adoption among Indonesian students: awareness is moderate but uncertainty persists, mirroring a broader national pattern in which Indonesian digital regulation has been described as reactive rather than proactively adaptive (Bani Adam, 2025), and marked by normative disharmony between repressive and restorative orientations across other areas of Indonesian digital governance (Ginting et al., 2026), suggesting institutional and national guidance need to develop in tandem.

4.7. Measurement Model Assessment and Common Method Bias

The measurement model was assessed before testing structural relationships, using the listwise-complete analytic subset (N = 178). Convergent validity, internal consistency, and discriminant validity were evaluated for the seven reflective constructs in Table 4, with results reported in Table 9.

Table 9. Measurement Model: Internal Consistency and Convergent Validity

Construct	Indicators (loading range)	alpha	CR	AVE
PE	Q19d-Q19g (0.77-0.80)	0.802	0.869	0.623
SAT	Q24e-Q24g, Q25b-Q25d (0.61-0.79)	0.802	0.859	0.504
AILIT	Q28h, Q28i, Q29d, Q29e, Q29i (0.72-0.87)	0.847	0.890	0.619
USE	Q15, Q18a, Q18i, Q18k (0.65-0.81)	0.767	0.850	0.589
ENG	Q26e, Q26f, Q26h, Q27e, Q27h (0.76-0.82)	0.849	0.892	0.623
INT	Q22b, Q22c, Q22d, Q22j (0.73-0.96)	0.908	0.933	0.779
REG	Q21a-Q21d (0.71-0.81)	0.757	0.845	0.577

All standardized outer loadings exceeded 0.61, composite reliability ranged from 0.85 to 0.93, and average variance extracted ranged from 0.50 to 0.78, satisfying conventional reliability and convergent-validity thresholds (Hair et al., 2019). Discriminant validity is reported in Table 10.

Table 10. Discriminant Validity (Fornell-Larcker criterion; diagonal = square root of AVE)

	PE	SAT	AILIT	USE	ENG	INT	REG
PE	0.79						
SAT	0.47	0.71					
AILIT	0.40	0.60	0.79				
USE	0.34	0.43	0.37	0.77			
ENG	0.47	0.64	0.72	0.26	0.79		
INT	0.08	0.09	0.03	0.01	-0.03	0.88	
REG	0.19	0.13	0.18	0.04	0.15	0.19	0.76

The square root of AVE on each diagonal exceeded corresponding inter-construct correlations, and all HTMT ratios were below 0.85 (maximum 0.837 for AILIT-ENG), a close association acknowledged as a limitation of discriminant separation, though the criterion was met.

Common method bias was examined via Harman's single-factor test, which produced a first factor explaining 26.9% of variance (below the 50% threshold), and full-collinearity VIFs ranging from 1.06 to 2.57 (below the 3.3 criterion), indicating common method bias is not a material concern.

4.8. Structural Model and Hypothesis Testing

The structural model was estimated using the path-weighting scheme, with significance assessed through 500 bootstrap resamples and percentile 95% confidence intervals. Table 11 reports standardized path coefficients, confidence intervals, t-values, effect sizes, and hypothesis outcomes, with the model depicted in Figure 7.

Table 11. Structural Model Results and Hypothesis Testing (N = 178; 500 bootstrap resamples)

Path	beta	95% CI	t	f2	Outcome
H1: PE -> SAT	0.473	[0.309, 0.636]	5.41	0.289	Supported
H2: SAT -> USE	0.268	[0.046, 0.457]	2.44	0.053	Supported
H3: PE -> USE	0.152	[-0.017, 0.326]	1.70	0.022	Not supported
H4: AILIT -> USE	0.145	[-0.058, 0.358]	1.37	0.017	Not supported
H5: AILIT -> ENG	0.714	[0.636, 0.792]	14.68	0.905	Supported
H6: USE -> ENG	0.003	[-0.148, 0.134]	0.04	0.000	Not supported
H7: USE -> INT	0.004	[-0.128, 0.153]	0.06	0.000	Not supported
H8: AILIT -> INT	-0.012	[-0.223, 0.192]	-0.11	0.000	Not supported
H9: REG -> INT	0.191	[-0.248, 0.349]	1.25	0.037	Not supported

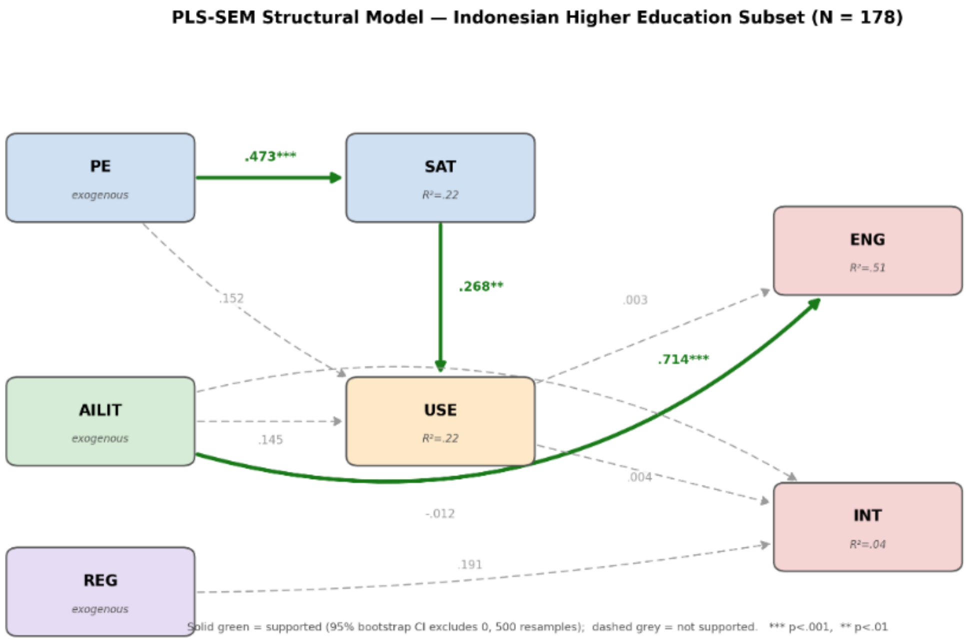

Figure 7. PLS-SEM Structural Model with Standardized Path Coefficients (N = 178)

The technology-acceptance chain was supported: perceived capability predicted satisfaction (beta = 0.473, $p < .001$), which predicted adoption (beta = 0.268, $p < .01$), confirming H1-H2. The strongest relationship was literacy's effect on engagement (beta = 0.714, $p < .001$; f2 = 0.905), supporting H5 and explaining 51.2% of engagement variance; explained variance was 0.224 for satisfaction, 0.219 for adoption, and 0.036 for integrity.

GenAI adoption did not significantly predict engagement (H6 not supported), perceived capability and literacy did not predict adoption directly (H3-H4 not supported), and no paths to integrity concern reached significance (H7-H9 not supported), indicating that literacy, not usage intensity, governs engagement.

4.9. Robustness and Global Benchmarking

To benchmark the Indonesian findings, construct composites were compared with the rest-of-world sample using Mann-Whitney U tests, appropriate for ordinal, non-normally distributed data, with rank-biserial r and Cohen's d as effect sizes, reported in Table 12 and Figure 8.

Table 12. Indonesian Subset Versus Global Baseline (Mann-Whitney U with effect sizes)

Construct	M (ID)	M (Global)	U	p	rank-biserial	Cohen d
PE	3.51	3.63	1,325,678	0.004	0.118	-0.182
SAT	3.31	3.46	1,106,876	<0.001	0.165	-0.221
AILIT	3.31	3.31	1,151,242	0.37	0.038	-0.006
USE	2.53	2.53	1,636,061	0.66	-0.018	0.006
ENG	3.35	3.41	1,169,709	0.079	0.074	-0.065
INT	3.21	3.10	1,451,306	0.22	-0.051	0.105
REG	3.33	3.31	1,355,415	0.55	0.024	0.023

Indonesian students reported slightly lower perceived capability ($d = -0.18$, $p = .004$) and satisfaction ($d = -0.22$, $p < .001$) than the global baseline; other constructs did not differ significantly (all $|d| <= 0.11$), indicating a perception-behavior gap consistent with the broader global pattern.

4.10. Sociotechnical Synthesis of GenAI Adoption in Indonesian Higher Education

The findings show GenAI adoption is a sociotechnical process: students showed more favorable attitudes than usage-frequency scores, consistent with sociotechnical perspectives that technologies are embedded within institutional arrangements rather than adopted in isolation (Trist & Bamforth, 1951; Bostrom & Heinen, 1977; Orlikowski, 1992; Baxter & Sommerville, 2011).

Adoption is literacy-dependent, since digital and AI literacy bridges favorable perceptions and responsible practice (Long & Magerko, 2020; Ng et al., 2021; Shiri, 2024); engagement outcomes were moderate-to-positive but conditional; and academic integrity remains a central concern given moderate awareness but substantial uncertainty about acceptable use (Cotton et al., 2023; Eke, 2023; Sullivan et al., 2023; Perkins et al., 2024). This sociotechnical interpretation is the main contribution of the study: GenAI adoption is shaped not just by whether students use ChatGPT, but by how such use is guided and governed, requiring coordinated action from students, lecturers, institutions, and policymakers.

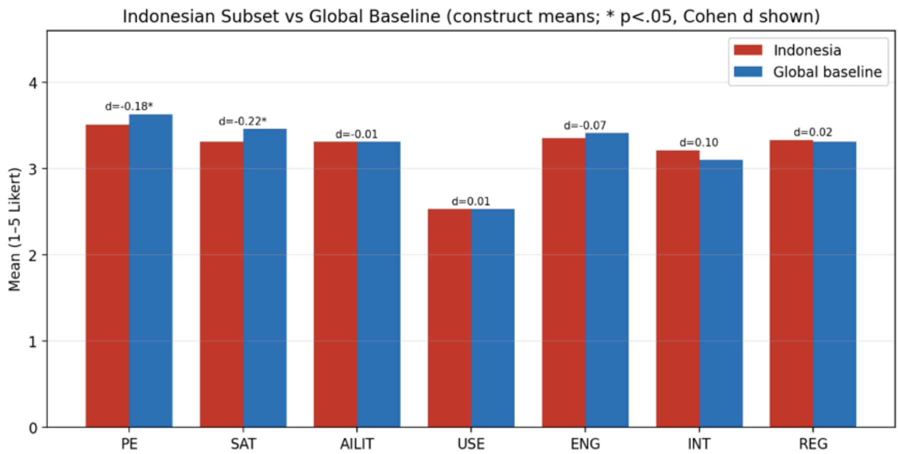

Figure 8. Construct Means: Indonesian Subset Versus Global Baseline

5. Conclusion

This study analyzed Generative AI adoption in Indonesian higher education through a sociotechnical perspective, using an Indonesian subset (N = 270). GenAI adoption was already evident but not yet intensive: students showed more favorable satisfaction and attitude scores than usage-frequency scores, and digital and AI literacy was the strongest predictor of student engagement, while usage intensity had no significant effect.

These results should be read in light of limitations: the listwise-complete subset (N = 178) is adequate for medium-sized effects but underpowered for small structural paths, and the data are concentrated in three institutions, so confirmatory studies with larger, regionally stratified samples are warranted.

Digital and AI literacy is a central condition for responsible GenAI adoption and should be a strategic priority for higher-education policy and teaching practice; the study's main contribution is its sociotechnical interpretation showing that adoption is shaped by the interaction of perception, usage, literacy, engagement, integrity, and institutional support.

This study is limited by its reliance on secondary data that may not be nationally representative; future research should use larger, more representative Indonesian samples. Practically, institutions should develop clear GenAI policies, strengthen AI-literacy programs, support assessment redesign, and promote responsible academic use of AI.

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