

Exploratory Factor Analysis of Generative AI Usage in The Learning Process at Telkom University Surabaya

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ABSTRACT

Purpose – The rapid development of generative artificial intelligence (generative AI) has driven its increased use in higher education, particularly to support learning activities, academic task completion, and information searching. This study aims to examine the empirical factor structure of a questionnaire on generative AI usage in the learning process, and to assess the extent to which this structure corresponds to the five technology acceptance constructs (TAM/UTAUT) used to design the instrument. The sample was drawn solely from active students at the Telkom University Surabaya Campus.

Methods – The study used a quantitative cross-sectional survey of 150 students selected through purposive sampling. A 25-item questionnaire built on five TAM/UTAUT-based constructs was administered online and analyzed using Exploratory Factor Analysis (EFA) with Principal Component Analysis (PCA) extraction and Varimax rotation. Data adequacy was tested using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity.

Findings – The data were suitable for EFA (KMO = 0.803; Bartlett's Test of Sphericity, $p < 0.001$). Five components were retained, namely Perceived Benefit, Perceived Ease, Motivation and Interest in AI Usage, Trust and Concerns toward AI, and Social Environment Influence, which together explain 65.650% of the total variance. Because these five components correspond to the five constructs used to design the instrument, the results provide initial support for the instrument's dimensional structure rather than evidence of newly discovered factors or of factors that influence AI usage.

Research Implications – The results may inform institutional discussions on generative AI literacy that consider technical, psychological, and social aspects. The study is limited by its single institution, purposive sampling, self-reported data, cross-sectional design, and the absence of confirmatory validation. Further studies should apply CFA or SEM to an independent sample.

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Introduction

The development of artificial intelligence (AI) technology in recent years has brought significant changes to various sectors, including at Telkom University Surabaya. The emergence of generative AI technologies such as ChatGPT, Google Gemini, and Microsoft Copilot enables students to obtain information, understand course material, generate ideas, and complete various academic tasks more quickly and efficiently. This transformation shows that AI no longer functions merely as a technological aid, but has become an integral part of modern learning activities. Therefore, understanding the patterns and factors associated with generative AI usage in educational settings has become an increasingly important issue to investigate (Syafitra & Asmara, 2025). In this article, “generative AI” refers to the chatbot-type platforms assessed by the research instrument, whereas “AI” is used for the broader technology and for cited studies that do not specify the type of AI.

In Indonesia, AI use among students is already widespread. A survey by Tirto and Jakpat among 1,501 school and university students aged 15–21 years found that 86.21% of respondents used AI to complete assignments at least once a month (Hartanto & Rohmah, 2024). This phenomenon indicates that AI has become a learning instrument widely used by the younger generation. This condition presents an opportunity to improve learning effectiveness through faster access to information, learning personalization, and increased academic productivity (Abdaljaleel et al., 2024).

Nevertheless, the high rate of AI adoption has also sparked various debates among academics. On one hand, AI is considered capable of improving the quality of the learning process by providing quick information, supporting task completion, and increasing learning efficiency (Foroughi et al., 2024; Huda et al., 2024). On the other hand, uncontrolled use of AI has the potential to create dependency, reduce critical thinking ability, diminish creativity, and weaken students’ learning independence (Fan et al., 2025; Firdaus et al., 2024; Hou et al., 2025). These differing views show that AI usage behavior is associated not only with technological characteristics, but also with psychological, social, and environmental factors that shape users’ decisions in utilizing the technology (Fan et al., 2025).

Previous studies on the factors associated with AI usage in learning can be grouped into two strands. The first strand is grounded in the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and their extensions. It mostly tests hypothesized relationships among predefined constructs using structural equation modeling, for example among higher education students (Almogren et al., 2024), across five Indonesian universities (Habibi et al., 2024), and among school students (Li et al., 2024); one further study explored UTAUT constructs qualitatively through interviews (Menon & Shilpa, 2023). In these studies, perceived usefulness, ease of use, feedback

quality, and subject norms were reported to be related to students' attitudes and intention to use ChatGPT (Almogren et al., 2024). Descriptive studies in Indonesia likewise report ease of information access and response speed as driving factors of AI use and limited digital literacy as an inhibiting factor (Firdaus et al., 2024), as well as perceived improvements in the effectiveness and efficiency of students' learning (Huda et al., 2024).

The second strand uses factor analysis to develop and validate questionnaires. Exploratory factor analysis has been applied to measure students' experiences with AI in academic writing among medical students (Khojasteh et al., 2025), the opportunities and challenges of ChatGPT use in education (Taktak & Bafrali, 2025), and attitudes toward generative AI (Marengo et al., 2025). These instruments were developed outside Indonesia and target outcomes other than TAM/UTAUT-based acceptance constructs. In Indonesia, an exploratory study identified seven factors in students' choice of AI tools, but it relied on a small sample (about 70 respondents) and a low KMO value (0.56) and did not use TAM/UTAUT as its framework (Savanah et al., 2024). Among the studies reviewed here, those built on TAM/UTAUT are predominantly confirmatory, and none has examined the factor structure of a TAM/UTAUT-based questionnaire on generative AI usage among Indonesian university students using EFA. Confirmatory approaches test predetermined relationships, so they cannot show whether the assumed constructs separate empirically in a new context; exploratory evidence of this kind therefore remains limited.

This research gap is relevant for students at the Telkom University Surabaya Campus. As prospective professionals who are required to process information and make data-based decisions, these students need to use generative AI effectively and responsibly. However, none of the studies reviewed here has mapped how students at this campus perceive generative AI along the dimensions commonly used in technology acceptance research. This lack of information can make it difficult for educational institutions to design learning strategies and digital literacy programs that suit users' needs.

Based on this problem, this study applies Exploratory Factor Analysis (EFA) to examine the empirical factor structure of a questionnaire on generative AI usage among active students at the Telkom University Surabaya Campus. Specifically, it checks whether the five TAM/UTAUT-based constructs used to design the instrument (Davis, 1989; Venkatesh et al., 2003) re-emerge as distinct dimensions in the data, as a preliminary assessment of the instrument's dimensionality. The study does not aim to discover new constructs, and it does not test relationships among constructs or the causes of AI usage; these require confirmatory and structural analyses in later research. The results are expected to contribute to the development of studies on AI technology acceptance in higher education, as well as serve as a basis for institutions in formulating digital literacy policies and strategies that support the optimal, ethical, and sustainable use of AI.

Methods

1. Research Design

This study uses a quantitative approach with a cross-sectional survey design. The quantitative approach was chosen because the research focuses on measuring students' perceptions of generative AI usage through numerical data analyzed statistically. Exploratory Factor Analysis (EFA) was used as the main technique to examine how the 25 questionnaire indicators group into empirically derived factors (Hair et al., 2019; Rozy, 2025). Because the items were originally organized around five theory-based constructs from TAM and UTAUT, the analysis serves as a preliminary check on the dimensionality of the instrument: it examines whether this a priori grouping is supported by the data, rather than searching for a factor structure without a theoretical starting point or testing relationships among constructs. The number of factors was not fixed in advance; it was determined from the data using the eigenvalue criterion and the scree plot.

2. Population and Sample

The research population consists of all active students at Telkom University Surabaya Campus who have used at least one generative AI platform, such as ChatGPT, Google Gemini, Microsoft Copilot, or Perplexity AI, in their academic learning activities.

The sampling technique was carried out using *purposive sampling* (Khoiroh et al., 2026) with the following respondent criteria: (1) being an active student at the Telkom University Surabaya Campus; (2) having experience using a generative AI platform to support academic activities; and (3) being willing to complete the questionnaire in full. The sample size was determined based on the recommendation that the number of respondents for factor analysis should be at least five times the number of indicators used (Hair et al., 2019). With 25 research indicators, the minimum sample size is 125 respondents. To improve the stability of the factor analysis results, this study involved 150 respondents. Of these respondents, 87 were women (58.0%) and 63 were men (42.0%). By cohort, 23 respondents (15.3%) were from the class of 2021, 30 (20.0%) from 2022, 56 (37.3%) from 2023, and 41 (27.3%) from 2024. The main generative AI platform used was ChatGPT (72 respondents, 48.0%), followed by Google Gemini (45, 30.0%), Grammarly (14, 9.3%), Microsoft Copilot (14, 9.3%), and Perplexity AI (5, 3.3%). In terms of frequency of use, 43 respondents (28.7%) used AI every day, 49 (32.7%) four to six times a week, 32 (21.3%) one to three times a week, and 26 (17.3%) several times a month.

3. Data Collection

The research instrument is a closed questionnaire developed based on the theoretical review of the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and adapts several indicators from previous research on the acceptance and use of AI in higher education. The 25 statements were worded in Indonesian for the context of

academic learning. Perceived Ease and Perceived Benefit follow the perceived ease of use and perceived usefulness constructs of TAM, and Social Environment Influence follows the social influence construct of UTAUT. Motivation and Interest in AI Usage and Trust and Concerns toward AI draw on the literature on students' motivation, trust, and risk awareness regarding AI discussed in the Introduction and Discussion. TAM explains that technology acceptance is related to perceived usefulness and perceived ease of use, while UTAUT adds the role of social influence and facilitating conditions in technology use.

The questionnaire consists of 25 statements representing five initial constructs, namely Perceived Ease (P1–P5), Perceived Benefit (P6–P10), Motivation and Interest in AI Usage (P11–P15), Social Environment Influence (P16–P20), and Trust and Concerns toward AI (P21–P25). The construct labels follow the original wording of the instrument. Each statement was measured using a five-point Likert scale, namely 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. This scale was chosen because it is effective in measuring respondents' attitudes, perceptions, and level of agreement toward a phenomenon. All items were analyzed using their original 1–5 scores. The statements in the Trust and Concerns toward AI block were all worded in the same positive direction, including the concern-related statements (P22–P24), which were phrased as reassurance (for example, not being worried about depending on AI). Higher scores therefore consistently indicate greater trust and less concern, and no item was reverse-scored.

Table 1. Questionnaire Rating Scale

Number	Description	Code
1	Strongly Disagree	SD
2	Disagree	D
3	Neutral	N
4	Agree	A
5	Strongly Agree	SA

Primary data were collected online using the Google Forms platform. The questionnaire link was distributed through various digital communication media, such as WhatsApp and Instagram. Data collection was conducted until the targeted number of respondents was met. The use of an online survey was chosen because it allows for a wider reach of respondents, efficient data collection time, and ease of data processing. Before completing the questionnaire, respondents were informed of the purpose of the study and gave their consent to participate voluntarily; their responses were collected anonymously, used solely for the purposes of this research, and reported only in aggregate form. Before the factor analysis was conducted, the item-level validity and reliability of the instrument were examined on the full sample. Item validity was assessed using corrected item-total correlations, that is, the Pearson product-moment correlation between each item and the total score of the remaining items. An item is declared valid if

its coefficient is greater than the critical value at a 5% significance level. Reliability was assessed using Cronbach's Alpha, computed for the whole instrument and for each factor retained; an alpha of ≥ 0.70 indicates adequate internal consistency (Yusup, 2018).

4. Data Analysis

The data were analyzed using IBM SPSS Statistics. Before extraction, data adequacy was examined using the Kaiser-Meyer-Olkin (KMO) measure, Bartlett's Test of Sphericity, and the Measures of Sampling Adequacy (MSA) of each indicator from the anti-image matrices; the data were considered adequate if the KMO and MSA values exceeded 0.50 and the significance of Bartlett's Test was below 0.05 (Hair et al., 2019).

Factors were then extracted using Principal Component Analysis (PCA). PCA was selected because the analysis is intended to empirically examine the number and composition of the item groups formed by the 25 indicators as a check on the instrument's dimensionality, rather than to estimate latent constructs net of measurement error, which would call for a common-factor method such as Principal Axis Factoring (Hair et al., 2019). Components were retained if they had an eigenvalue ≥ 1.00 according to the Kaiser criterion, and the number retained was checked against the scree plot and the cumulative variance explained (Sukserm, 2025).

The retained components were rotated using the Varimax method (orthogonal rotation) with Kaiser normalization to produce a simpler and more easily interpretable factor structure. Varimax was chosen because the five theoretical constructs underlying the instrument are conceptually distinct dimensions in TAM/UTAUT, so the factors were assumed to be relatively uncorrelated for the sake of interpretive simplicity; this rotation maximizes the variance of the factor loadings so that each indicator has a clearer association with a particular component. Studies that wish to allow the resulting factors to correlate could instead consider an oblique rotation such as Direct Oblimin.

Finally, the rotated solution was interpreted on the basis of factor loadings and communalities. An indicator was considered to have an adequate contribution to a factor if it had a factor loading ≥ 0.50 and a communality ≥ 0.50 , and the resulting factors were named according to the characteristics of the indicators with the highest loadings on each factor.

Result

This section reports the analyses in the order in which they were carried out: the validity and reliability of the instrument, the data adequacy tests (KMO, Bartlett's Test of Sphericity, and the Measures of Sampling Adequacy), communalities, factor extraction, and factor rotation. All analyses were run in IBM SPSS Statistics using the responses of the 150 students.

1. Validity Test

The validity test aims to determine each indicator's ability to measure the construct under study. It was performed using *corrected item-total correlation* in the *Reliability Analysis* menu, and the results are presented in Table 2. The coefficients ranged from .054 to .410. Most indicators exceeded the approximate critical value ($r\text{-table} \approx 0.160$ for $n = 150$, $\alpha = 0.05$), but four items (P11, P14, P22, and P24) fell below this threshold and therefore did not meet the validity criterion stated in the Methods. These items were nevertheless retained for the factor analysis because each loaded at 0.70 or above on the component it was written for (Table 10) with communalities of at least 0.555 (Table 7), and because deleting any one of them would raise Cronbach's Alpha only marginally (to between .704 and .711). They remain weak items that warrant revision in future refinements of the instrument (Yusup, 2018).

Table 2. Item-Total Statistics (Validity Test)

Item	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
P1	.336	.688
P2	.410	.682
P3	.392	.683
P4	.340	.687
P5	.346	.687
P6	.279	.693
P7	.233	.696
P8	.296	.691
P9	.332	.688
P10	.325	.689
P11	.125	.704
P12	.215	.697
P13	.189	.699
P14	.093	.706
P15	.265	.693
P16	.192	.699
P17	.378	.684
P18	.221	.697
P19	.262	.694
P20	.204	.698
P21	.186	.700
P22	.054	.711
P23	.233	.696
P24	.097	.707
P25	.196	.699

Note. $n = 150$. Critical value ($r\text{-table}$) ≈ 0.160 at $\alpha = 0.05$.

2. Reliability Test

The reliability test was performed using Cronbach's Alpha to determine the internal consistency of the research instrument, as presented in Table 3. The alpha for all 25 items was 0.704, only slightly above the 0.70 minimum, and the alpha based on standardized items was 0.707 (Yusup, 2018). Because a single coefficient for the whole instrument says little about each factor, reliability was also computed separately for the five factors (Table 4). Cronbach's Alpha ranged from .817 (Social Environment Influence) to .894 (Perceived Benefit), so all five factors exceeded the 0.70 criterion and showed good internal consistency. The modest alpha of the combined 25 items therefore appears to reflect the multidimensional structure of the instrument rather than weak consistency within each factor.

Table 3. Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.704	.707	25

Table 4. Reliability Statistics per Factor

Factor	Items	N of Items	Cronbach's Alpha
Perceived Benefit	P6–P10	5	.894
Perceived Ease	P1–P5	5	.880
Motivation and Interest in AI Usage	P11–P15	5	.872
Trust and Concerns toward AI	P21–P25	5	.831
Social Environment Influence	P16–P20	5	.817

Note. Cronbach's Alpha was computed separately for the items loading on each component in Table 10.

3. Data Adequacy Test (KMO and Bartlett's Test)

Before the factor analysis was conducted, the data were tested using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity (Table 5). The KMO value was 0.803, which is greater than 0.50, so the data are declared adequate for analysis using Exploratory Factor Analysis. Bartlett's Test of Sphericity yielded a Chi-Square value of 1757.898 (df = 300, $p < 0.001$). Since the significance value is smaller than 0.05, the correlation matrix is not an identity matrix, so the data meet the requirements for factor analysis.

Table 5. KMO and Bartlett's Test

Test	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.803
Bartlett's Test of Sphericity: Approx. Chi-Square	1757.898
df	300
Sig.	< .001

4. Anti-Image Matrices

The Anti-Image Matrices were used to examine the Measures of Sampling Adequacy (MSA) of each indicator, taken from the diagonal of the anti-image correlation matrix and summarized in Table 6. All 25 indicators produced MSA values between .738 and .873, well above the minimum threshold of 0.50, so all indicators meet the requirement to be retained in the factor analysis.

Table 6. Measures of Sampling Adequacy (MSA) from the Anti-Image Correlation Matrix

Item	MSA	Item	MSA
P1	.765	P14	.813
P2	.813	P15	.830
P3	.852	P16	.790
P4	.792	P17	.741
P5	.805	P18	.749
P6	.822	P19	.754
P7	.873	P20	.776
P8	.806	P21	.754
P9	.839	P22	.823
P10	.808	P23	.738
P11	.806	P24	.818
P12	.823	P25	.760
P13	.850		

Note. MSA values are the diagonal entries of the anti-image correlation matrix.

5. Communalities

Communalities show how much of the variance of each variable is explained by the factors formed, as presented in Table 7. All indicators have extraction values above 0.50. The highest communality is found in indicator P10 (.778), and the lowest in indicator P20 (.519). This shows that all indicators are reasonably well explained by the components retained.

Table 7. Communalities (Extraction Method: Principal Component Analysis)

Item	Extraction	Item	Extraction
P1	.656	P14	.681
P2	.720	P15	.657
P3	.669	P16	.615
P4	.696	P17	.632
P5	.695	P18	.608
P6	.702	P19	.587
P7	.610	P20	.519
P8	.716	P21	.647
P9	.733	P22	.624
P10	.778	P23	.645
P11	.701	P24	.555
P12	.648	P25	.648
P13	.671		

6. Factor Extraction

Factors were extracted using Principal Component Analysis (PCA). As shown in Table 8, five components had eigenvalues greater than 1: 3.971, 3.866, 3.183, 2.914, and 2.478. They explain 15.886%, 15.463%, 12.731%, 11.657%, and 9.913% of the variance, respectively, and 65.650% cumulatively, which exceeds the 60% commonly used as a minimum benchmark in the social sciences (Hair et al., 2019). The sixth component had an eigenvalue of 0.727 and was not retained. After Varimax rotation, the explained variance was redistributed across the five components (11.854% to 14.272%).

Table 8. Total Variance Explained (Extraction Method: Principal Component Analysis)

Component	Eigenvalue	% Var.	Cum. %	Rotated Eigenvalue	Rotated % Var.	Rotated Cum. %
1	3.971	15.886	15.886	3.568	14.272	14.272
2	3.866	15.463	31.349	3.429	13.714	27.986
3	3.183	12.731	44.080	3.411	13.645	41.630
4	2.914	11.657	55.737	3.041	12.166	53.796
5	2.478	9.913	65.650	2.964	11.854	65.650

Note. Var. = variance; Cum. = cumulative. Eigenvalue = initial eigenvalue, which equals the extraction sum of squared loadings; the rotated columns are the rotation sums of squared loadings (Varimax). Components 6–25 had eigenvalues below 1.00 (0.180 to 0.727) and are not shown.

7. Factor Rotation

Factor rotation was carried out using the Varimax method with Kaiser normalization to obtain a factor structure that is easier to interpret. As shown in Table 10, each indicator had its highest loading on a single component, with loadings ranging from .702 to .878. Loadings on the other components were suppressed in the SPSS output, so cross-loadings cannot be evaluated from this table. The resulting grouping of indicators is summarized in Table 9.

Table 9. Factor Rotation Results

Component	Indicators	Factor Name
1	P6, P7, P8, P9, P10	Perceived Benefit
2	P1, P2, P3, P4, P5	Perceived Ease
3	P11, P12, P13, P14, P15	Motivation and Interest in AI Usage
4	P21, P22, P23, P24, P25	Trust and Concerns toward AI
5	P16, P17, P18, P19, P20	Social Environment Influence

Table 10. Rotated Component Matrix

Item	1	2	3	4	5
P1		.807			
P2		.831			
P3		.800			
P4		.823			
P5		.832			
P6	.834				
P7	.775				
P8	.844				
P9	.844				
P10	.878				
P11			.827		
P12			.798		
P13			.809		
P14			.806		
P15			.803		
P16					.773
P17					.777
P18					.772
P19					.753
P20					.712
P21				.797	
P22				.746	
P23				.785	
P24				.702	
P25				.798	

Note. Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization; Only the loading on the primary component is displayed.

Discussion

The Exploratory Factor Analysis (EFA) results show that students' perceptions of generative AI usage in the learning process at the Telkom University Surabaya Campus are organized into five components, namely Perceived Benefit, Perceived Ease, Motivation and Interest in AI Usage, Trust and Concerns toward AI, and Social Environment Influence. These five components cumulatively explain 65.650% of the variance, indicating that they capture a substantial share of the covariation among the items measuring students' perceptions of generative AI.

Two points frame how the results should be read. First, EFA and PCA describe patterns of covariation among questionnaire items; the size of a component's eigenvalue or variance share shows how strongly its items covary, not how important or how causal a factor is for AI usage. Second, the five factors obtained correspond exactly to the five constructs on which the instrument was built, so the results mainly indicate that the

blocks of items were empirically separable in this sample, rather than that new dimensions were discovered.

What the analysis adds beyond the assumed structure is limited but informative. As displayed in the rotated matrix, each of the 25 indicators loaded on only one component, with loadings from .702 to .878 and communalities from .519 to .778. The variance was spread fairly evenly across the five components (11.854% to 14.272% after rotation) rather than dominated by one, which suggests that no single component dominates the structure in this sample. The trust and concern items formed a component of their own, separate from perceived benefit and perceived ease, which supports treating them as a distinct dimension. At the same time, the low corrected item-total correlations of four items (P11, P14, P22, and P24) and the modest overall Cronbach's Alpha (0.704) show that the instrument still needs refinement.

The first component, Perceived Benefit, is a coherent group of items describing AI as a technology that helps students understand course material, speed up task completion, provide academic references, increase productivity, and support the quality of learning outcomes (Foroughi et al., 2024). Its position as the first component reflects how strongly its items covary; it does not mean that perceived benefit is the most important factor or a causal determinant of AI usage. The grouping is consistent with the perceived usefulness construct of the Technology Acceptance Model (Davis, 1989), which has been linked to technology acceptance in earlier studies (Biloš & Budimir, 2024; Pasupuleti et al., 2026), and with reports that AI is perceived to improve the effectiveness and efficiency of students' learning (Huda et al., 2024). Whether perceived benefit is related to actual usage cannot be concluded from this analysis and needs to be tested in a structural model.

The second component, Perceived Ease, shows that students' perceptions of AI as easy to learn, easy to operate, and not requiring complex technical skills covary as a distinct group of items. Ease of access and interaction through conversation-based interfaces allows students to obtain information quickly and practically. This finding is consistent with the Perceived Ease of Use construct in TAM (Davis, 1989), which has been associated with technology acceptance (Pasupuleti et al., 2026). Prior studies likewise report that perceived ease is related to students' attitudes toward ChatGPT (Almogren et al., 2024). This pattern suggests that ease of use remains a relevant dimension to consider in the adoption of AI-based learning technology.

The third component, Motivation and Interest in AI Usage, indicates that students' interest and perceived learning experience form a group of items distinct from functional benefit. AI can provide responses that are fast, interactive, and relevant to students' learning needs, which may be related to their engagement and motivation in the learning process (Azizah & Nugraha, 2025). The separation of this component from Perceived

Benefit suggests that the development of AI-based learning needs to consider the aspect of user experience, although the present data cannot show how motivation is related to usage.

The fourth component, Trust and Concerns toward AI, combines two aspects that the literature treats as related but distinct: trust in AI's ability to provide information and assist with academic task completion (Rahman et al., 2023), and awareness of risks associated with AI use, such as information inaccuracy, potential bias, violations of academic ethics, and dependency on technology (Musyaffi et al., 2024). Psychological factors such as perceived risk and attitudes toward AI have also been proposed to shape students' trust in AI-based learning assistants (Dağtekin & Erkalkan, 2025), and UTAUT2-based models of AI adoption have been extended with psychological and contextual factors (Ballestra Caffaratti et al., 2025). All five items of this component (P21–P25) have positive loadings (.702 to .798).

Because the concern-related items (P22–P24) were worded as reassurance and no item was reverse-scored (see Methods), the single component indicates that greater trust goes together with lower concern, that is, one confidence–wariness dimension. That trust and concern did not separate into two factors may partly reflect this shared positive wording as well as a genuine confidence–wariness dimension. The pattern reflects covariation among responses and does not explain why the items group together; whether trust and concern are better modeled as one factor or two should be tested in a confirmatory model on an independent sample. The finding suggests that students' perceptions of AI are associated not only with benefit and ease of use, but also with trust in the quality of the information produced, which is in line with studies emphasizing the role of trust in the adoption of AI technology (Rahman et al., 2023). Therefore, improving AI literacy and information verification skills may be a useful focus in the implementation of AI in higher education settings (Musyaffi et al., 2024).

The fifth component, Social Environment Influence, groups items on the views and support of students' surrounding academic environment, including peers, lecturers, and the prevailing academic culture (Mistry et al., 2025). This is in line with the Social Influence construct in UTAUT, which explains that individuals' perceptions of others' views can be related to technology usage decisions (Venkatesh et al., 2003), and which has been linked to generative AI adoption intentions in earlier studies (Korchak et al., 2025). The present data show only that these items covary as a distinct group; they do not show that social support increases students' AI usage. Institutions may nonetheless consider the academic environment when discussing the appropriate and responsible use of AI.

The results show that students' perceptions of generative AI usage in learning at this campus are multidimensional, spanning technological, psychological, and social aspects. These findings are consistent with the view that factors beyond technology also form part

of how students perceive AI in higher education, although the cross-sectional, self-report design cannot show that these factors shape usage behavior. The practical implication of this research is that educational institutions may consider AI literacy policies and programs that not only emphasize the benefits and ease of use, but also raise students' awareness of ethics, information validity, and responsible AI use (Cabero-Almenara et al., 2024).

This study has several limitations. First, all respondents came from a single campus, Telkom University Surabaya, so the findings cannot be generalized to other institutions or disciplines. Second, respondents were selected through purposive sampling, which may not represent all students who use generative AI. Third, the data are self-reported perceptions and may be affected by social desirability and recall bias. Fourth, the cross-sectional design captures perceptions at a single point in time. Fifth, the analysis is exploratory: the factors identified describe covariation among items and should not be read as factors that influence AI usage, since EFA does not test causal effects. Sixth, no confirmatory validation has been carried out; a later CFA should use a different sample from the one used for this EFA so that validation does not rely on the same data. Finally, the instrument itself needs refinement, as the overall Cronbach's Alpha was modest (0.704), several items had low corrected item-total correlations, and the choice of PCA with an orthogonal Varimax rotation may have produced a cleaner structure than a common-factor extraction with oblique rotation would.

Conclusion

This study examined the factor structure of the questionnaire used to measure the use of generative Artificial Intelligence (AI) in the learning process of active students at Telkom University Surabaya Campus. Exploratory Factor Analysis (EFA) with Principal Component Analysis extraction and Varimax rotation on 150 respondents produced five factor groups, namely Perceived Benefit, Perceived Ease, Motivation and Interest in AI Usage, Trust and Concerns toward AI, and Social Environment Influence. The data were adequate for factor analysis (KMO = 0.803; Bartlett's Test of Sphericity, $p < 0.001$), and the five factors explain 65.650% of the total variance. Because these five factors correspond to the five constructs used to design the instrument, the results provide initial empirical support for the instrument's dimensional structure rather than evidence of new constructs or of factors that influence AI usage. The findings indicate that students' perceptions of AI usage in learning are structured along technological (perceived benefit and ease), psychological (motivation and interest, trust and concerns), and social dimensions. This is consistent with the view that AI acceptance in higher education is multidimensional, although the cross-sectional, self-report design cannot show that these dimensions affect students' AI usage.

In practical terms, the results may serve as a starting point for higher education institutions to consider AI literacy programs that focus not only on technology usage skills, but also on critical thinking, information evaluation, and ethical and responsible AI use. Lecturers may use these findings as a reference when considering how to integrate AI into the learning process. Future research is recommended to include respondents from various higher education institutions and disciplines to improve generalizability. Confirmatory Factor Analysis (CFA) should be conducted on a separate, independent sample rather than on the data used for this EFA, and Structural Equation Modeling (SEM) can then be used to test hypothesized relationships between the factors, which EFA cannot do.

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