Balancing Benefit and Sacrifice: A Dual-Path TAM-VAM Integration to Explain Students' Intention to Use Gemini AI in Higher Education

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Abstract: While generative AI reshapes higher education, understanding the psychological trade-offs that drive students' digital use remains critical. Because the Intention-to-Use items in this study ask about continuing to use Gemini AI throughout one's studies rather than about a first-time adoption decision, the construct is best understood as a continuance-oriented usage intention rather than an initial-adoption intention. This study integrates the Technology Acceptance Model (TAM) and the Value-based Adoption Model (VAM) to examine how perceived benefits and sacrifices relate to students' attitudes, perceived value, and ultimate intention to use Gemini AI. Using a quantitative survey approach, data from 248 university students in East Java who had experience with Gemini AI in academic tasks were analysed using PLS-SEM in SmartPLS 4. The structural model explained 54.5% of the variance in Intention to Use (R^2 = .545), 41.9% in Attitude (R^2 = .419), and 37.3% in Perceived Value (R^2 = .373). Perceived Benefit was significantly and positively associated with both Attitude (β = .638, p < .001) and Perceived Value (β = .602, p < .001), whereas Perceived Sacrifice showed a smaller but statistically significant negative association with both constructs (β = −.115 and −.113, p < .05). Both Perceived Value and Attitude, in turn, significantly and positively predicted Intention to Use (β = .348 and .451, p < .001), with a larger coefficient for Attitude. Bootstrapped indirect effects were all significant (via Attitude and Perceived Value, respectively: β = .288 and .209 for Perceived Benefit; β = −.052 and −.039 for Perceived Sacrifice), with the attitudinal route carrying a somewhat larger share. Theoretically, this research synthesizes value and cognitive-affective pathways, offering a holistic framework for Gemini AI usage intention that jointly captures calculative cost–benefit evaluation and affective attitude formation, thereby extending single-pathway adoption models. To our knowledge, this is among the first tests of an integrated dual-path VAM–TAM model for a generative, conversational AI tool in an emerging higher-

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education market, clarifying the relative weight of value-based versus attitudinal routes. In practice, the findings suggest that AI developers and educators must actively minimize user sacrifices while maximizing the functional academic utility to foster sustainable digital usage in university ecosystems. The findings further highlight that sustainable AI adoption requires not only perceived usefulness but also institutional support, ethical guidance, and student AI literacy.

Keywords: Gemini AI, Technology Acceptance Model, Value-based Adoption Model, Intention to Use, Higher Education.

Introduction

Artificial intelligence has moved rapidly from a peripheral tool to a central part of how students find information, conduct research, and complete academic work. Google's Gemini AI is a multimodal system that can process and produce text, images, and other media (Rane et al., 2024; Team., 2025). Heavy reliance on generative AI is not without cost, however: it raises concerns about plagiarism, hallucinated misinformation, over-dependence on AI output, and weakened critical thinking (Francis et al., 2025; Kofinas et al., 2025). Weighing these benefits against these risks, which bear on students' intention to use AI, has therefore become an important issue for researchers and educational institutions. Technology acceptance research has long asked what makes people adopt and use a given technology. The Technology Acceptance Model (TAM) is the most familiar answer, explaining usage in terms of how users perceive and feel about a technology (Davis., 1987). Yet some researchers argue that attitude alone does not explain adoption, and that the value people believe they obtain matters just as much as how they feel (Kim et al., 2007). To explain how users evaluate technology, the Value-Based Adoption Model (VAM) posits that technology use decisions hinge on a trade-off between perceived benefits and perceived sacrifices (Kim et al., 2007). Users compare the benefits of using a technology with the risks or effort involved, and the result forms Perceived Value (Zeithaml., 1988), which in turn informs behavioral intentions. VAM has been applied successfully to students' adoption of AI technologies, highlighting the role of perceived value in usage-related intentions (Rruplli et al., 2024). Combining VAM with TAM has been used to explain students' acceptance of chatbots and ChatGPT (Al-Abdullatif., 2023; Al-Abdullatif & Alsubaie., 2024) and of e-learning systems (Liao et al., 2022), with perceived value emerging as a key predictor of use intention. This study builds on that integration to explain students' intention to use Gemini AI. Through the VAM lens, students weigh the benefits against the sacrifices of using Gemini AI, which informs their

Perceived Value (Kim et al., 2007). Through the TAM lens, those same evaluations likely also inform students' Attitude toward Using Gemini AI, which in turn relates to their intention to use it (Davis., 1987). Together, the two perspectives give a fuller picture of how cognitive evaluation and attitude jointly relate to students' Intention to Use (Al-Abdullatif., 2023). Recent empirical work on generative-AI adoption in higher education covering ChatGPT adoption (Abdalla et al., 2024; Mahmud et al., 2024; Lai et al., 2024), generative-AI governance (Barus et al., 2025), and academic-integrity risk (Kofinas et al., 2025; Francis et al., 2025) has examined adoption mainly through acceptance-model, governance, or risk lenses and, to our knowledge, has rarely modelled the benefit and sacrifice sides of the adoption trade-off jointly. Although previous studies have examined generative AI adoption through TAM-type or VAM-type perspectives, limited research has examined how students simultaneously balance academic benefits and AI-related sacrifices, such as ethical concerns, reliability risks, and institutional consequences, particularly for a generative and conversational system such as Gemini AI. Gemini AI differs from conventional educational technologies in that its outputs are generative rather than fixed, which introduces adoption-relevant considerations, including hallucination risk, over-reliance, and academic-integrity exposure, that earlier TAM- or VAM-only studies of static or transactional technologies did not need to address. Beyond adoption intention itself, higher education institutions must also ensure responsible AI practices through AI literacy, ethical guidelines, and governance mechanisms that address academic integrity risks; this study's dual-path model, by explicitly incorporating Perceived Sacrifice, provides an empirical basis for such responsible-AI considerations. Examining this dual-path mechanism within the higher education context of East Java, Indonesia, is theoretically meaningful because Indonesian universities are undergoing rapid, largely unregulated generative AI adoption alongside an emerging digital-learning transformation and nascent institutional AI governance policies, making student-level evidence on benefit–sacrifice trade-offs particularly timely for shaping AI-related academic policy (Barus et al., 2025). Existing TAM–VAM integrations in education have examined e-learning (Liao et al., 2022), chatbots (Al-Abdullatif., 2023), and ChatGPT (Al-Abdullatif & Alsubaie., 2024). The present study differs in focusing on Gemini AI and in modelling Perceived Benefit and Perceived Sacrifice simultaneously as antecedents of both Perceived Value and Attitude, so that the value-based and attitudinal routes to Intention to Use can be compared directly and their indirect effects tested with bootstrapping; to our knowledge, this comparison has not yet been reported for Gemini AI. This study contributes to the literature in several ways by simultaneously examining the dual-path mechanism through which Perceived Value and Attitude toward Using Gemini AI shape students' continuance usage intention within a single integrated VAM-TAM model. Theoretically, by

empirically testing this dual-path mechanism, the study clarifies the relative explanatory power of value-based and attitudinal pathways in university students' usage of generative AI. Practically, the findings offer empirical guidance for universities, AI developers, and policymakers seeking to support the sustained use of Gemini AI in academic settings, particularly within the higher education context of East Java, Indonesia. Specifically, this study aims to (1) test a dual-path VAM–TAM model in which Perceived Benefit and Perceived Sacrifice simultaneously predict Perceived Value and Attitude toward Using Gemini AI, and (2) examine the relative strength of the value-based and attitudinal pathways, including their indirect effects, in predicting students' Intention to Use Gemini AI.

Methods

Model and Hypothesis Development

A quantitative cross-sectional survey formed the basis of this study, aimed at examining how Perceived Benefit, Perceived Sacrifice, Perceived Value, Attitude toward Using Gemini AI, and Intention to Use Gemini AI relate to each other. The research model draws on both the Value-Based Adoption Model (VAM) and the Technology Acceptance Model (TAM). A quantitative design fit this purpose since it allows hypothesized relationships among latent variables to be tested and theoretical models evaluated statistically (Hair et al., 2019). In this dual-path structure, Perceived Benefit and Perceived Sacrifice act as the two starting points that simultaneously feed into Perceived Value through the VAM pathway and Attitude toward Using Gemini AI through the TAM pathway. Perceived Value and Attitude then jointly serve as the two proximal predictors of Intention to Use Gemini AI. The proposed research model is illustrated in Figure 1.

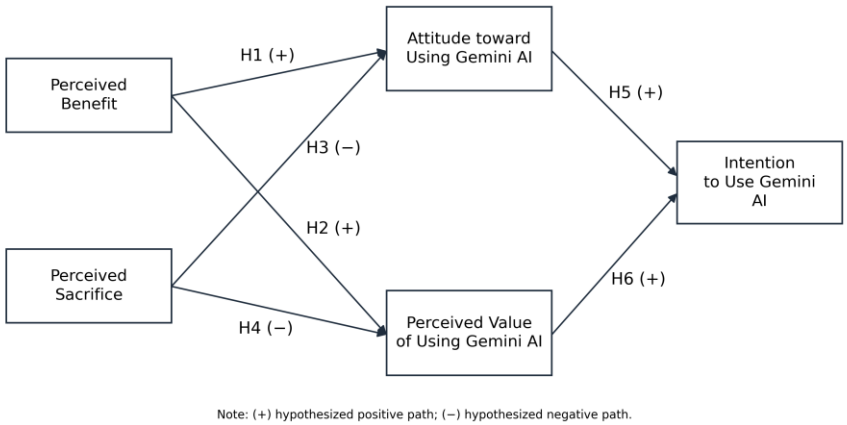


Figure 1 Proposed Research Model

The model retains Attitude toward Using Gemini AI as the sole TAM-derived construct rather than incorporating the conventional Perceived Usefulness and Perceived Ease of Use

antecedents (Davis., 1989), because Perceived Benefit, as operationalized here, already captures the usefulness-oriented appraisal that Perceived Usefulness represents in the original TAM, while ease-of-use considerations are less salient for a conversational, natural-language interface such as Gemini AI, where interaction largely mirrors ordinary text-based dialogue rather than requiring a distinct interface skill; retaining Attitude alone therefore avoids conceptual redundancy between Perceived Usefulness and Perceived Benefit while preserving the affective-evaluative pathway that TAM contributes to the model. The direct paths from Perceived Benefit and Perceived Sacrifice to Attitude (H1, H3) are grounded in the expectancy–value account of attitude formation, in which attitude toward a behavior is formed from beliefs about the consequences of that behavior and how desirable those consequences are, so that perceived benefits (positive consequences) and perceived sacrifices (negative consequences) can shape Attitude directly, independent of any intervening value judgment (Ajzen., 1991); this justifies specifying Attitude as a direct outcome of Perceived Benefit and Perceived Sacrifice rather than only as a downstream consequence of Perceived Value. Perceived Sacrifice itself is conceptualized, consistent with VAM, as the composite of cognitive and social costs a student anticipates from using Gemini AI operationalized here as output-bias risk, erosion of others' trust in one's academic work, and exposure to academic-integrity sanctions rather than the monetary or effort-based sacrifices emphasized in VAM's original mobile-internet context. Based on the theoretical foundations of VAM and TAM, and consistent with prior empirical evidence (Al-Abdullatif., 2023; Rruplli et al., 2024), the following hypotheses are proposed:

H1: Perceived Benefit positively and significantly predicts Attitude toward Using Gemini AI. Students who find Gemini AI useful and enjoyable are expected to evaluate its use more favorably, because attitude is formed from beliefs about the consequences of a behavior and how desirable they are (Ajzen., 1991; Al-Abdullatif., 2023).

H2: Perceived Benefit positively and significantly predicts Perceived Value of Using Gemini AI. Under VAM, the benefits received are weighed in forming overall value (Kim et al., 2007; Zeithaml., 1988), and usefulness and enjoyment have been identified as significant antecedents of the perceived value of ChatGPT in learning (Al-Abdullatif & Alsubaie., 2024).

H3: Perceived Sacrifice negatively and significantly predicts Attitude toward Using Gemini AI. Perceived sacrifice (integrity, bias, and social-trust risks) is expected to lower attitude through the same expectancy–value mechanism (Ajzen., 1991).

H4: Perceived Sacrifice negatively and significantly predicts Perceived Value of Using Gemini AI. Under VAM, sacrifices reduce perceived value (Kim et al., 2007; Zeithaml., 1988);

evidence for risk-type sacrifices is mixed, since perceived risk was not a significant predictor of value in some ChatGPT studies (Al-Abdullatif & Alsubaie., 2024), which is why the size of this path is examined empirically.

H5: Attitude toward Using Gemini AI positively and significantly predicts Intention to Use Gemini AI. TAM positions attitude as the proximal evaluation that precedes behavioral intention (Davis., 1987), and this link is expected to hold for continued use of Gemini AI.

H6: Perceived Value of Using Gemini AI positively and significantly predicts Intention to Use Gemini AI. VAM expects perceived value to predict adoption intention (Kim et al., 2007), and perceived value has been reported as a strong predictor of students' intention to use ChatGPT (Al-Abdullatif & Alsubaie., 2024; Rruplli et al., 2024).

Across these six hypotheses, H1 and H3 specify the direct, attitude-formation effects (TAM pathway) of Perceived Benefit and Perceived Sacrifice, while H2 and H4 specify the parallel, value-based effects (VAM pathway) of the same two antecedents; H5 and H6 then specify the proximal, direct effects of Attitude and Perceived Value on Intention to Use. None of these six paths is itself a mediating (indirect) effect; the mediating role of Attitude and Perceived Value in the relationship between Perceived Benefit/Sacrifice and Intention to Use is tested separately, as an indirect effect, in the Mediation Analysis subsection below.

Questionnaire Development

Data were collected via a self-administered online questionnaire comprising two sections. The first section collected demographic information, including institution of origin, Gemini AI usage status, purpose of use, recency of use, and frequency of use. The second section measured the research constructs using multiple-item scales adapted from previous studies. Perceived Benefit items were adapted from (Mahmud et al., 2024) and (Gupta., 2020). Perceived Sacrifice items were adapted from (Ivanov et al., 2024) and (Lai et al., 2024). Perceived Value items were adapted from (Gupta., 2020) and (Sohn & Kwon., 2020). Attitude toward Using Gemini AI items were adapted from (Abdalla et al., 2024). The Intention to Use Gemini AI items were adapted from (Lee et al., 2025). All items were assessed using a six-point Likert scale ranging from 1 (Strongly Disagree) to 6 (Strongly Agree). The summary of the measurement instrument is presented in Table 1. Because the source items were originally developed for other technologies (mobile learning, ChatGPT, and MOOC platforms), each item's wording was contextually adapted by replacing the original referenced technology with "Gemini AI" and rephrasing generic terms (e.g., "chatbot", "the system") into Gemini-specific academic-use language (e.g., "using Gemini AI for academic activities"); the adapted wording was then reviewed for face validity in the Gemini AI context

before distribution. The Perceived Value items follow the logic of the VAM operationalization of value as benefit relative to effort and time (Kim et al., 2007). The Perceived Sacrifice construct is measured with three indicators, following the item count used by (Ivanov et al., 2024) and (Lai et al., 2024) for comparable risk-oriented constructs; while a three-item scale can under-represent a broader construct, the measurement model results reported below (outer loadings 0.821–0.922, composite reliability = 0.915) show that the three items consistently and strongly capture the construct as operationalized here. At the same time, these three items only cover output-bias, social-trust, and academic-sanction risk, and likely under-represent other Gemini AI-specific sacrifices such as over-reliance, privacy, and data-security concerns as a limitation revisited in the Conclusion. Indicator adequacy was further verified empirically through outer loadings, cross-loadings, and discriminant validity, as reported in the Measurement Model Assessment subsection.

Table 1 Measurement Instrument

Variable	Indicator	Statement	Source
Perceived Benefit	PB1	In my opinion, using Gemini AI for academic activities will be a satisfying experience.	(Mahmud et al., 2024)
	PB2	I believe that using Gemini AI can improve the effectiveness of my learning in college.	(Gupta, 2020)
	PB3	In general, the use of Gemini AI in academic activities provides positive benefits for me as a student.	(Mahmud et al., 2024)
Perceived Sacrifice	PS1	I am concerned that the answers generated by Gemini AI may contain bias.	(Ivanov et al., 2024)
	PS2	I feel that the use of Gemini AI may reduce others' confidence in the results of my academic work.	
	PS3	I am afraid that I will be subject to academic sanctions such as reduced grades for being considered to have committed plagiarism if I use Gemini AI.	(Lai et al., 2024)
Perceived Value	PV1	Using Gemini AI provides benefits that are worth my efforts.	(Gupta, 2020)
	PV2	The time I spent using Gemini AI yielded comparable results.	
	PV3	Compared to the effort I would have needed to do manually, Gemini AI provides significant benefits.	(Sohn & Kwon, 2020)
Attitude	AT1	Using Gemini AI to support academic activities is a positive decision.	(Abdalla et al., 2024)
	AT2	Using Gemini AI in lectures or assignments is a smart decision.	
	AT3	I have a positive impression of using Gemini AI in my academic and work activities.	
Intention to Use Gemini AI	IU1	I will always try to use Gemini AI in my daily academic activities at college.	(Lee et al., 2025)
	IU2	I plan to continue using Gemini AI throughout my studies at college.	
	IU3	I plan to use Gemini AI regularly to support my learning.	

Sample Selection and Data Collection

University students in East Java, Indonesia who had used Gemini AI for academic purposes made up the target population. Given that respondents needed to meet certain criteria tied directly to the research objectives, purposive sampling was used. Eligibility required being (1) an active university student and (2) having used Gemini AI for academic work at least once in the past month. The size of the sample was determined using the ten-times rule common in PLS-SEM, which says the sample should be at least ten times the largest number of structural paths pointing at any one endogenous construct (Hair et al., 2019). For example the Attitude toward Using Gemini AI, Perceived Value and Intention to Use Gemini AI each have two paths that point to them. Thus, putting the minimum required sample at 20 respondents, a bar the final sample of 248 responses cleared by a wide margin. Beyond the ten-times rule, sample adequacy was also considered against statistical-power benchmarks for multiple regression with two predictors per endogenous construct (Cohen., 1988). Detecting a medium effect size ($f^2 = .15$) at $\alpha = .05$ with 80% power requires a minimum sample of about 68, while detecting a small effect ($f^2 = .02$) under the same criteria would require approximately 490 respondents. The achieved sample of 248 therefore provides ample power (> .99) to detect the medium-to-large effects associated with the Perceived Benefit paths ($f^2 \approx 0.58–0.70$). For the smaller Perceived Sacrifice paths ($f^2 \approx 0.02–0.03$), power at N = 248 is only about .50–.66 (calculated for a regression with two predictors at $\alpha = .05$), so these effects were detected near the limit of the design and should be interpreted cautiously, and smaller sacrifice effects could not have been reliably detected. This effect-size-based assessment offers a stronger justification for the sample size than the ten-times rule alone. The data was collected between October and December 2024 through an online questionnaire self-administered via Google Forms. The link was circulated on WhatsApp, X (formerly Twitter), TikTok, and Instagram to widen its reach among students. A total of 248 responses were received. The questionnaire opened with screening questions on the origin of the respondent's institution (East Java), prior use of Gemini AI, and use of Gemini AI for academic activities; all 248 respondents met these criteria, and the dataset contained no missing values, so all 248 responses were retained for analysis. Respondents were informed of the study's purpose beforehand, with assurance that their answers would remain anonymous and confidential. The 248 valid respondents were all active students at higher-education institutions in East Java who had used Gemini AI for academic purposes (Table 2). The largest institutional groups were Universitas Airlangga (n = 46, 18.5%), Universitas Brawijaya (n = 44, 17.7%), Universitas Negeri Surabaya (n = 32, 12.9%), Universitas Negeri Malang (n = 25, 10.1%), Universitas Internasional Semen Indonesia (n = 20, 8.1%), Universitas Muhammadiyah Malang (n = 12, 4.8%), and Institut Teknologi Sepuluh Nopember (n = 9, 3.6%); the remaining 60 respondents (24.2%) came from

other institutions. Most respondents were relatively recent users: 139 (56.0%) had started using Gemini AI less than one week earlier, 40 (16.1%) less than one month earlier, and 69 (27.8%) more than one month earlier. Over the previous month, 73 respondents (29.4%) used Gemini AI 1–2 times per week, 87 (35.1%) 3–5 times per week, and 88 (35.5%) more than five times per week. Gender and semester were not recorded in the questionnaire and therefore cannot be reported (see Limitations).

Table 2 Respondent Profile (N = 248)

Characteristic	Category	n	%
Institution	Universitas Airlangga	46	18.5
	Universitas Brawijaya	44	17.7
	Universitas Negeri Surabaya	32	12.9
	Universitas Negeri Malang	25	10.1
	Universitas Internasional Semen Indonesia	20	8.1
	Universitas Muhammadiyah Malang	12	4.8
	Institut Teknologi Sepuluh Nopember	9	3.6
	Other institutions	60	24.2
Time since first use	Less than 1 week	139	56.0
	Less than 1 month	40	16.1
	More than 1 month	69	27.8
Use in the past month	1–2 times per week	73	29.4
	3–5 times per week	87	35.1
	More than 5 times per week	88	35.5

Statistical Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test the model, run through SmartPLS 4 (Ringle et al., 2024). This method suits prediction-oriented research well, handles complex models, and allows the measurement and structural components to be assessed together (Hair et al., 2019; Subhaktiyasa, 2024). Significance testing of outer loadings and path coefficients was performed using complete bootstrapping (Hair et al., 2019) with 5,000 subsamples, the percentile bootstrap confidence interval method, a one-tailed test at the 5% significance level (appropriate because all six hypotheses are directional), parallel processing, and a fixed random seed for reproducibility. Confidence intervals for HTMT and for indirect effects therefore span the 5th to 95th percentiles. The PLS-SEM algorithm used the path weighting scheme, initial weights of 1.0, a maximum of 3,000 iterations, and a stop criterion of 10^{-7}. Discriminant validity was assessed with the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT; Henseler et al., 2015; Franke & Sarstedt, 2019), using HTMT < 0.90 as the conservative threshold. Because SmartPLS 4 does not implement the blindfolding procedure, predictive assessment was based on PLSpredict (10 folds, 10 repetitions, fixed seed; Shmueli et al., 2019), reporting Q^2predict

for each endogenous construct and comparing PLS-SEM prediction errors (RMSE) against a linear-model benchmark. The analysis followed the two-stage PLS-SEM procedure recommended by (Hair et al., 2019), starting with the measurement model before moving to the structural model. Indicator reliability, internal consistency reliability, convergent validity, and discriminant validity were all part of the measurement model evaluation. Internal consistency reliability was checked using Cronbach's Alpha and Composite Reliability, both expected to sit above 0.70. Convergent validity was gauged through Average Variance Extracted (AVE), with 0.50 as the cutoff. Discriminant validity followed the Fornell–Larcker criterion, meaning a construct is considered adequately distinct when the square root of its AVE is larger than its correlations with every other construct (Fornell & Larcker., 1981). On the structural side, path coefficients and the coefficient of determination (R^2) were used for evaluation, and were tested through bootstrapping, counted as supported when the p-value fell below 0.05 (Hair et al., 2019).

Results And Discussions

Measurement Model (Outer Model) Assessment

Before testing the hypothesized structural relationships, the measurement model was evaluated first to confirm each indicator genuinely represented its underlying construct. This meant checking indicator reliability (outer loadings), internal consistency reliability (Cronbach's Alpha and Composite Reliability), and convergent validity (AVE), all against the thresholds which (Hair et al., 2019) recommend. As presented in Table 3, outer loadings across all fifteen indicators ranged from 0.756 to 0.922, comfortably above the 0.70 minimum which confirms each indicator did its job representing its construct. Internal consistency reliability held up well too, with Cronbach's Alpha running from 0.708 (Perceived Benefit) to 0.865 (Perceived Sacrifice) and Composite Reliability from 0.837 (Perceived Benefit) to 0.915 (Perceived Sacrifice), both well past the 0.70 mark. Convergent validity was backed by AVE values between 0.632 and 0.782, all clearing the 0.50 threshold (Hair et al., 2019). Altogether, all five constructs (Perceived Benefit, Perceived Sacrifice, Perceived Value, Attitude toward Using Gemini AI, and Intention to Use Gemini AI) show solid reliability and convergent validity.

Table 3 Measurement Model Assessment

Indicators	Indicator Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Perceived Benefit (PB)				
PB1	0.845	0.708	0.837	0.632
PB2	0.782			
PB3	0.756			

Perceived Sacrifice (PS)				
PS1	0.922	0.865	0.915	0.782
PS2	0.906			
PS3	0.821			
Perceived Value (PV)				
PV1	0.811	0.768	0.866	0.683
PV2	0.851			
PV3	0.817			
Attitude (AT)				
AT1	0.856	0.763	0.863	0.678
AT2	0.785			
AT3	0.827			
Usage Intention (UI)				
UI1	0.864			
UI2	0.883	0.839	0.903	0.757
UI3	0.862			

For discriminant validity, the Fornell–Larcker criterion was applied, under which a construct is considered discriminantly valid if the square root of its AVE is greater than its correlations with every other construct in the model (Fornell & Larcker., 1981). Table 4 shows this held for each construct: Attitude (0.823), Perceived Benefit (0.795), Perceived Sacrifice (0.884), Perceived Value (0.827), and Intention to Use Gemini AI (0.870) each exceeded their correlations with any other construct. Attitude's value of 0.823, for example, was higher than its correlations with Perceived Benefit (0.637), Perceived Sacrifice (−0.109), Perceived Value (0.703), and Intention to Use Gemini AI (0.696). Together, these results confirm that all five constructs are empirically distinct, meeting the requirement for discriminant validity.

Table 4 Discriminant Validity (Fornell-Larcker Criterion)

	AT	**PB**	**PS**	**PV**	**UI**
AT	0.823				
PB	0.637	0.795			
PS	-0.109	0.009	0.884		
PV	0.703	0.601	-0.107	0.827	
UI	0.696	0.432	-0.149	0.665	0.870

As a complementary check, discriminant validity was also assessed with HTMT (Table 5). All HTMT values were below the conservative threshold of 0.90 except for the Perceived Value–Attitude pair (0.913). (Henseler et al., 2015) and (Hair et al., 2022) give 0.90 as the threshold for conceptually similar constructs, and (Henseler et al., 2015) add, as the inferential criterion, a bootstrapped confidence interval that excludes 1.00; (Franke and Sarstedt., 2019) found HTMT to perform in parallel with the constrained-phi approach when used in this way. The upper bounds of the bootstrap confidence intervals (5th–95th percentile, one-tailed) were below 1.00 for every pair; the highest was 0.987 for Perceived Value–Attitude (interval 0.839–0.987), followed by 0.947 for Perceived Benefit–Attitude, so discriminant

validity is supported by the inferential criterion. Using two-sided 95% intervals (2.5th–97.5th percentile) instead, the upper bound for Perceived Value–Attitude is 1.001, marginally including 1.00, while all other upper bounds stay below 1.00 (highest 0.962). The stricter test of whether the Perceived Value–Attitude ratio is significantly below 0.90 is not met, so the two constructs should be regarded as closely related, which is plausible given the theoretical proximity of value judgment and attitude, and this is acknowledged as a limitation.

Table 5 Discriminant Validity (Heterotrait–Monotrait Ratio, HTMT)

	AT	PB	PS	PV	UI
AT					
PB	0.860				
PS	0.130	0.084			
PV	**0.913**	0.813	0.130		
UI	0.865	0.563	0.189	0.825	

Because Perceived Sacrifice is measured with only three indicators, its measurement quality and the robustness of its structural effects were examined further. The three items are internally consistent (Cronbach's α = 0.864; composite reliability = 0.915; inter-item correlations between 0.65 and 0.73), and the construct is clearly distinct from the others (all HTMT values ≤ 0.189). As a sensitivity check, each item was dropped in turn and the Perceived Sacrifice paths were re-estimated with unweighted composite scores and ordinary least squares (an approximation to, not a replacement for, the PLS-SEM estimates). With all three items the standardized coefficients were −0.111 (Attitude) and −0.104 (Perceived Value); after dropping any single item they ranged from −0.096 to −0.120 for Attitude (one-tailed p = .008–.027) and from −0.092 to −0.108 for Perceived Value (p = .017–.036). The negative and significant Perceived Sacrifice effects were therefore retained in every two-item version, indicating that the findings do not hinge on any single indicator, although a broader sacrifice scale remains a recommended extension.

Structural Model (Inner Model) Assessment

With the measurement model confirmed as sound, the structural model was evaluated next to test the hypothesized relationships among Perceived Benefit, Perceived Sacrifice, Perceived Value, Attitude toward Using Gemini AI, and Intention to Use Gemini AI. This involved two steps: looking at the coefficient of determination (R^2) for each endogenous construct, then testing hypotheses through bootstrapping (Hair et al., 2019).

Coefficient of Determination (R^2)

Table 6 lays out the R^2 values for the model's three endogenous constructs. Intention to Use Gemini AI came out highest at 0.545, meaning Attitude toward Using Gemini AI and Perceived

Value together account for 54.5% of the variance in students' intention to use it. Attitude toward Using Gemini AI posted an R^2 of 0.419, with Perceived Benefit and Perceived Sacrifice jointly explaining 41.9% of its variance, while Perceived Value came in at 0.373, indicating that the same two predictors explained 37.3% of its variance. These results suggest that the proposed dual-path model has satisfactory explanatory power, particularly regarding Intention to Use Gemini AI.

Table 6 Coefficient of Determination

Endogenous Variable	R-Square
Attitude toward Using Gemini AI	0.419
Perceived Value of Using Gemini AI	0.373
Intention to Use Gemini AI	0.545

Predictive Power (PLSpredict)

Predictive power was assessed with PLSpredict (10 folds, 10 repetitions; Shmueli et al., 2019). Q^2predict was positive for all three endogenous constructs: Attitude (0.403), Perceived Value (0.359), and Intention to Use (0.193), indicating predictive relevance beyond the mean-prediction benchmark. At the indicator level, the PLS-SEM RMSE was lower than the linear-model benchmark for all nine indicators of the endogenous constructs (e.g., AT1: 0.780 vs. 0.797; PV1: 0.842 vs. 0.854; IA1: 1.078 vs. 1.082), which indicates high predictive power according to the guidelines of (Shmueli et al., 2019). The predictive power for Intention to Use is the lowest of the three, so the model should be read as explanatory first and moderately predictive for the final outcome.

Hypothesis Testing

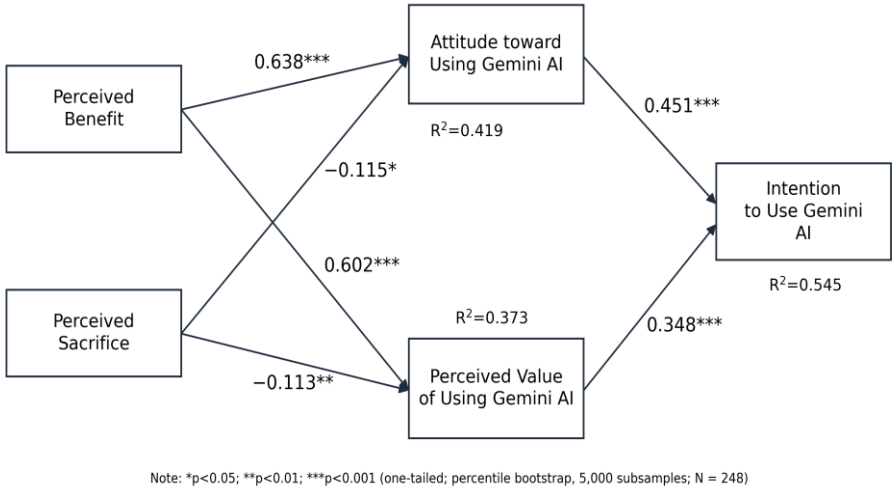


Figure 2 Hypothesis Testing Results (Bootstrapping)

Hypothesis testing was conducted using the bootstrapping procedure, in which a path was considered statistically significant when the one-tailed p-value was below 0.05, since every

hypothesis specifies a direction (Hair et al., 2019). The path coefficients, t-statistics, p-values, and effect sizes (f^2) for the six hypothesized relationships are illustrated in Figure 2 and summarized in Table 7. Because the data are cross-sectional, terms such as "effect" and "influence" are used here in their statistical sense (association or prediction within the specified model) and do not establish causation. For transparency, two-tailed p-values lead to the same decisions (H3 = .033, H4 = .018; indirect effects of Perceived Sacrifice via Attitude and Perceived Value = .044 and .033).

Table 7 Path Coefficient and Hypothesis Testing Results

Hypothesis	Path Coefficients	t-statistics	p-values	f^2	Decision
H1: PB → AT	0.638	14.586	0.000	0.700	Supported
H2: PB → PV	0.602	11.762	0.000	0.578	Supported
H3: PS → AT	-0.115	2.137	0.016	0.023	Supported
H4: PS → PV	-0.113	2.366	0.009	0.020	Supported
H5: AT → UI	0.451	6.476	0.000	0.226	Supported
H6: PV → UI	0.348	5.248	0.000	0.135	Supported

As shown in Table 7, all six hypotheses were statistically supported. Perceived Benefit was a strong positive predictor of Attitude toward Using Gemini AI ($\beta = 0.638$, $t = 14.586$, $p < .001$) and Perceived Value ($\beta = 0.602$, $t = 11.762$, $p < .001$), supporting H1 and H2. Based on (Cohen., 1988) benchmark for effect size ($f^2 \geq 0.02$ small, ≥ 0.15 medium, ≥ 0.35 large), both effects were large ($f^2 = 0.700$ and 0.578, respectively), indicating that students' perception of the academic usefulness and enjoyment of Gemini AI is strongly associated with both their attitude and their value judgment toward the technology. Perceived Sacrifice, by contrast, was a significant but comparatively small negative predictor of both Attitude ($\beta = -0.115$, $t = 2.137$, $p = .016$, $f^2 = 0.023$) and Perceived Value ($\beta = -0.113$, $t = 2.366$, $p = .009$, $f^2 = 0.020$), supporting H3 and H4. Although statistically significant, the small effect sizes suggest that concerns related to academic integrity risk, output bias, and social stigma are associated with a comparatively modest reduction relative to the strong positive pull of Perceived Benefit. This result is worth highlighting precisely because it qualifies, rather than contradicts, the hypothesized trade-off logic: the sacrifice pathway is real and significant, but substantially weaker than the benefit pathway. Because the sample is reasonably large ($N = 248$), even small coefficients can reach statistical significance, so practical importance was examined separately. Converting each f^2 into the change in explained variance ($\Delta R^2 = f^2 \times (1 - R^2)$ of the endogenous construct), removing Perceived Sacrifice would lower R^2 by only about 1.3 percentage points for Attitude (0.023×0.581) and about 1.3 points for Perceived Value (0.020×0.627), whereas removing Perceived Benefit would lower R^2 by about 41 points (0.700×0.581) and 36 points (0.578×0.627), respectively. In raw scale units, approximated with

unweighted composite scores on the six-point scale, a one-point increase in Perceived Sacrifice corresponds to a decrease of roughly 0.07 points in both Attitude and Perceived Value, whereas a one-point increase in Perceived Benefit corresponds to an increase of roughly 0.70 points in each. The Perceived Sacrifice paths are therefore statistically reliable but practically small: concerns about integrity, bias, and social trust are detectable in students' evaluations, yet on their own they are unlikely to shift attitudes or value judgments much and should not be read as a strong deterrent. Both mediating constructs subsequently were significant positive predictors of Intention to Use Gemini AI: Attitude ($\beta = 0.451$, $t = 6.476$, $p < .001$, $f^2 = 0.226$) and Perceived Value ($\beta = 0.348$, $t = 5.248$, $p < .001$, $f^2 = 0.135$), supporting H5 and H6 with medium effect sizes. Notably, the point estimate for Attitude was larger than that for Perceived Value, suggesting that, within this sample, the affective-evaluative pathway derived from TAM contributed more strongly to behavioral intention than the value-based cost–benefit pathway derived from VAM, although both pathways operated concurrently and significantly. A plausible explanation is that Intention to Use, as operationalized here (e.g., "I will always try to use…", "I plan to continue using…"), reflects an ongoing, habitual commitment rather than a one-off adoption decision; continuance-type intentions in the technology-use literature tend to be associated more with affective attachment (captured here by Attitude) than by a renewed calculative cost–benefit appraisal (captured by Perceived Value) once a technology is already part of a student's routine.

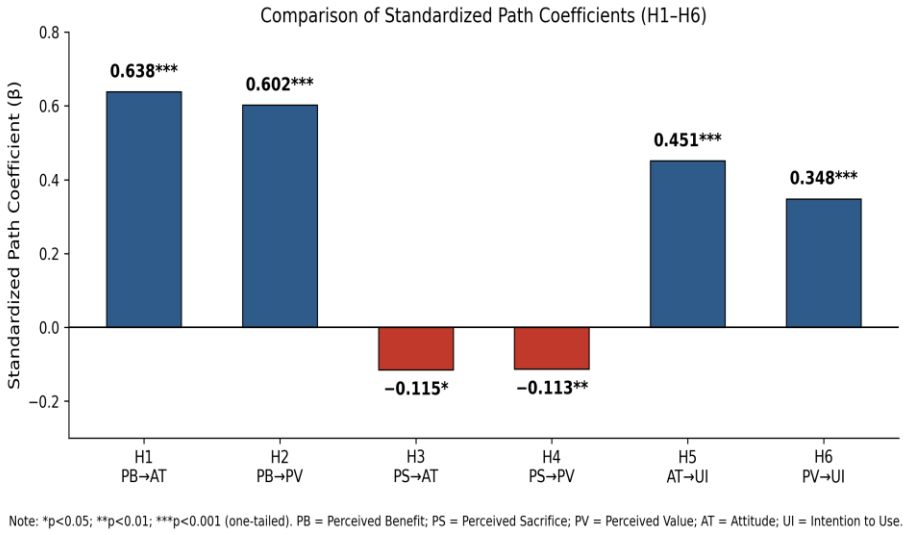


Figure 3 Comparison of the Six Standardized Path Coefficients (H1–H6)

As Figure 3 shows, the two Perceived Benefit paths (H1, H2) are markedly larger than the two Perceived Sacrifice paths (H3, H4), and both mediator-to-intention paths (H5, H6) fall in between, visually reinforcing the pattern already reported above: benefit-related appraisal dominates the model, sacrifice-related appraisal is real but comparatively small, and Attitude has a somewhat larger coefficient than Perceived Value as a predictor of Intention to Use.

Mediation Analysis

Because the structural model specifies no direct paths from Perceived Benefit or Perceived Sacrifice to Intention to Use, Attitude and Perceived Value operate as parallel mediators, and the four specific indirect effects were tested with bootstrapping (5,000 subsamples, percentile method, one-tailed). All four were statistically significant, and none of the 5th–95th percentile confidence intervals included zero: Perceived Benefit → Attitude → Intention to Use (β = 0.288, t = 5.575, p < .001, CI [0.204, 0.374]), Perceived Benefit → Perceived Value → Intention to Use (β = 0.209, t = 4.867, p < .001, CI [0.141, 0.283]), Perceived Sacrifice → Attitude → Intention to Use (β = −0.052, t = 2.016, p = .022, CI [−0.092, −0.012]), and Perceived Sacrifice → Perceived Value → Intention to Use (β = −0.039, t = 2.135, p = .016, CI [−0.070, −0.013]). The Attitude route carried the larger share of both the Perceived Benefit effect (0.288 vs. 0.209, about 58% of the total indirect effect of 0.497) and the Perceived Sacrifice effect (−0.052 vs. −0.039, about 57% of −0.091), so the two routes are complementary rather than redundant, with the attitudinal route somewhat dominant. The Benefit-based indirect effects were roughly five times larger in magnitude than the Sacrifice-based ones, mirroring the pattern of the structural paths. Because the model contains no direct paths from the exogenous constructs to Intention to Use, it cannot distinguish full from partial mediation; the indirect effects describe how the associations are transmitted through the two mediators as specified in the model.

Discussion

The findings support integrating the Value-Based Adoption Model (VAM) and Technology Acceptance Model (TAM) to explain students' Intention to Use Gemini AI, extending earlier TAM–VAM integrations in education (Al-Abdullatif., 2023; Liao et al., 2022). Where Attitude is commonly treated simply as something that follows from Perceived Value, this study finds that Perceived Benefit and Perceived Sacrifice are also directly and significantly related to Attitude on their own, separate from Perceived Value (H1, H3). That points to students' emotional read on Gemini AI being associated with these appraisals both directly and indirectly through their value judgments. In line with VAM (Kim et al., 2007) and earlier AI-adoption work (Rruplli et al., 2024), Perceived Benefit turned out to be the strongest predictor of both Attitude and Perceived Value, which fits with research on perceived usefulness and enjoyment in academic AI use (Azmi & Fithriani., 2025). Put simply, in the East Java higher-education setting, the academic payoff of using Gemini AI seems to outweigh worries about its costs. The dominance of Perceived Benefit is plausibly explained by students experiencing Gemini AI as directly reducing academic workload, improving learning efficiency, and supporting problem-solving on writing, research, and programming tasks, so that its perceived functional payoff is immediate and concrete, whereas the risks captured

under Perceived Sacrifice are comparatively abstract and delayed in consequence. This explanation is offered as a plausible, post hoc interpretation of the observed pattern of effect sizes rather than as a directly tested psychological mechanism; the survey did not measure temporal immediacy or risk salience, so confirming it would require an experimental or longitudinal design that manipulates or measures the timing of perceived benefits and sacrifices. Although Perceived Sacrifice significantly and negatively predicted both Attitude and Perceived Value, consistent with VAM's trade-off logic (Kim et al., 2007), its effect sizes were considerably smaller than those of Perceived Benefit. This suggests that while students remain aware of risks such as academic integrity, output bias, and social stigma, these concerns do not substantially offset perceived advantages, consistent with TAM–VAM studies of ChatGPT and chatbot use in which perceived risk was a weak or non-significant predictor (Al-Abdullatif., 2023; Al-Abdullatif & Alsubaie., 2024). That modest effect deserves some caution, though, since the Perceived Sacrifice items here only covered output bias, social trust, and the risk of academic sanctions, broader risks specific to generative AI, like privacy, data security, dependency, and misinformation, weren't measured, and could well pull the effect down further if future models included them. The size of the Perceived Benefit → Attitude coefficient ($\beta = 0.638$, $f^2 = 0.700$) deserves specific interpretation rather than description alone. Substantively, it indicates that in this sample how favorably students evaluate Gemini AI largely reflects how useful and enjoyable they find it: Perceived Benefit accounts for about 41 of the 41.9 percentage points of variance explained in Attitude. Three considerations suggest reading the magnitude with some caution. First, the Perceived Benefit items (usefulness and enjoyment appraisals) and the Attitude items are both evaluative judgments of the same tool and are therefore conceptually adjacent; their HTMT ratio is high (0.860), although it stays below 0.90 and its confidence interval remains below 1.00. Second, all respondents were active Gemini AI users who had already found the tool worth using, so the coefficient may be larger than in a general student population. Third, because benefit and attitude were reported by the same respondents at the same time, shared-method variance may inflate the association (see Limitations). The coefficient is therefore best read as evidence that perceived benefit is the principal correlate of attitude formation, not as a precise estimate of its causal strength. Both Attitude and Perceived Value came out as significant, positive predictors of Intention to Use Gemini AI, which backs up the dual-path structure and lines up with both the TAM idea that attitude sits close to intention (Davis., 1987) and the VAM idea that perceived value is linked to usage decisions (Kim et al., 2007). The point estimate for Attitude ($\beta = 0.451$) is larger than that for Perceived Value ($\beta = 0.348$), which may suggest that affective evaluation carries somewhat more weight than calculative cost–benefit assessment for this sample, consistent with similar generative AI research (Rane et al., 2024). This difference should be read cautiously, however: the two effects were not formally compared,

and the HTMT ratio for Perceived Value and Attitude (0.913) indicates that the two constructs are closely related. These findings can be related to earlier empirical work in several specific ways. First, the dominance of benefit over sacrifice matches the VAM logic established for mobile internet by (Kim et al., 2007), in which benefits raise and sacrifices lower perceived value, and it is consistent with (Rruplli et al., 2024), who report that perceived value in turn informs students' intention to adopt generative AI tools, and with (Al-Abdullatif and Alsubaie., 2024), who found a strong effect of perceived value on students' intention to use ChatGPT. Second, the modest sacrifice effect is in line with TAM–VAM studies of ChatGPT and chatbot use among university students, in which perceived risk was not a significant predictor of value or attitude (Al-Abdullatif., 2023; Al-Abdullatif & Alsubaie., 2024); however, the present results add that, when both routes are modelled simultaneously for Gemini AI, Attitude carries a somewhat larger share of the indirect effects of both Perceived Benefit and Perceived Sacrifice, so a value-only specification would understate how students' affective evaluations transmit these appraisals. Third, the strong perceived benefits are consistent with the qualitative evidence of (Azmi and Fithriani., 2025), whose student participants described Gemini AI as improving the structure, coherence, and revision of their academic writing, which is the kind of usefulness captured by the Perceived Benefit items. Fourth, the modest weight of sacrifice contrasts with the prominence given to integrity, bias, and equity risks in the review by (Francis et al., 2025): students in this sample acknowledge these risks but weigh them far less than the practical payoff, a gap that institutions may need to address through AI-literacy and integrity education rather than assuming students will self-regulate. Theoretically, these results push VAM–TAM integration further by showing Perceived Benefit and Perceived Sacrifice work through two separate, parallel routes as one value-based (through Perceived Value), one attitudinal (through Attitude) that would together be associated with usage intention. Practically speaking, this means AI developers, university administrators, and policymakers should look for interventions that build up perceived academic benefit (say, showing concrete examples of how Gemini AI helps with writing, research, or problem-solving) while also tackling sacrifice-related worries (bias, integrity risk, stigma) through clear guidelines and AI-literacy training, since hitting both pathways at once is likely to work better than focusing on just one.

Conclusion

This study examined how Perceived Benefit and Perceived Sacrifice relate to university students' Intention to Use Gemini AI through two parallel pathways: a value-based pathway via Perceived Value and an attitudinal pathway via Attitude. All six hypothesized relationships were supported. Perceived Benefit was the dominant predictor of both mediators, Perceived

Sacrifice a significant but practically small negative predictor, and both Perceived Value and Attitude significantly predicted Intention to Use (R^2 = .545); all four indirect effects were significant, with the attitudinal route somewhat larger. The main contribution is to show, within a single model, that cost–benefit evaluation and affective evaluation are complementary rather than competing routes to generative AI usage intention. Because the model was tested on one cross-sectional sample and was not compared against rival specifications, it is offered as a well-supported account rather than a demonstrably more complete one than single-mediator models. Several limitations should be considered. First, the cross-sectional design and the purposive sample of East Java students who had already used Gemini AI limit causal interpretation and generalizability and may inflate coefficients through self-selection; the relationships reported are associations, and longitudinal or experimental designs are needed to establish direction. Second, all constructs were self-reported in one questionnaire at one time point; Harman's single-factor test across the 15 model indicators showed that the first factor accounted for 39.9% of the variance (below the 50% guideline), but this is a weak diagnostic, so common method bias cannot be ruled out. Third, the R^2 values for Attitude (0.419) and Perceived Value (0.373) leave more than half of their variance unexplained, pointing to omitted factors such as social influence, institutional policy, trust, or AI literacy. Fourth, Perceived Sacrifice was measured with three items covering bias, social-trust, and academic-sanction risk only, so a broader scale (privacy, dependency, cost) should be validated, and the close relationship between Perceived Value and Attitude (HTMT = 0.913; two-sided upper bound 1.001) calls for caution when comparing their effects. Fifth, because the model has no direct paths to Intention to Use, future work should test competing models with direct paths to establish whether the mediation is full or partial. Sixth, gender and semester were not recorded, and the analysis did not test differences across discipline, institution, or usage frequency; multi-group or moderation analyses would map the model's boundaries. Beyond these points, the findings speak to responsible AI use in higher education. Because students weigh Gemini AI's benefits far more heavily than its risks, universities should pair efforts to promote its academic usefulness with investment in AI literacy, clear ethical-use guidelines, and transparent institutional AI policy, so that adoption comes with informed, responsible use rather than uncritical reliance. The main implication for higher education is that sustaining responsible use depends on institutional attention to AI literacy, academic integrity safeguards, and governance alongside the functional benefits students already perceive.

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