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When AI self-efficacy meets self-regulation: Conditional pathways to academic procrastination

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Abstract

The increasing use of artificial intelligence (AI) tools in academic tasks has highlighted the need to understand how students' self-efficacy regarding these technologies relates to academic procrastination, particularly in relation to self-regulatory processes and patterns of AI use. This cross-sectional survey study examined the mediating role of self-control and self-management processes in the relationship between preservice teachers' AI self-efficacy and academic procrastination, as well as the moderating role of AI use frequency in these indirect relationships. The study included 506 preservice teachers. Direct and indirect relationships among the variables and conditional indirect effects were examined using mediation (Model 4) and conditional process (Model 14) analyses in Hayes's PROCESS v5.0 macro. The findings showed that direct and indirect associations with academic procrastination varied across AI self-efficacy dimensions, with self-evaluation emerging as a significant statistical mediator. Assistance self-efficacy was indirectly associated with lower academic procrastination through both self-monitoring and self-evaluation, whereas anthropomorphic interaction was indirectly associated with higher academic procrastination through self-evaluation. The indirect associations through self-evaluation were smaller in magnitude at higher levels of AI use frequency. These findings suggest that AI self-efficacy should be considered alongside students' self-regulatory processes and patterns of AI use when examining academic procrastination. They also highlight the potential value of educational programs that address the purposes, stages, and boundaries of academic AI use alongside technical skills.

Keywords: Academic procrastination; Conditional process analysis; AI self-efficacy; AI use frequency; Self-regulation

1. Introduction

The rapid integration of artificial intelligence (AI) into higher education has substantially transformed how students access information, produce academic content, and solve problems (Besalti, 2025; Hermita et al., 2026; Wang & Xu, 2026). AI tools that provide personalized feedback and dynamic learning support have been reported to enhance student engagement, academic productivity, and self-directed learning experiences (Aydan, 2026; Lahmer, 2025; Liu et al., 2026). Despite these positive developments, the widespread adoption of AI in education has also introduced a notable paradox. The educational affordances of AI do not automatically ensure that students will manage academic tasks more effectively or sustain their learning in a more self-regulated manner. On the contrary, overreliance on AI has been associated with risks such as offloading cognitive effort to technology, weakening critical thinking skills, and undermining academic integrity (Hermita et al., 2026; Kasneci et al., 2023; Miao & Holmes, 2023). Although AI tools can facilitate certain stages of academic tasks, intensive use may inadvertently delay task initiation or completion and has been associated with academic procrastination (Canieso et al., 2025). Consistent with this pattern, most students reportedly use AI to a limited extent, whereas those who use it intensively for academic tasks tend to develop greater dependence on these tools (Galindo-Domínguez et al., 2026). Students' attitudes toward AI have also been shown to be associated with academic procrastination, with this relationship shaped by individual psychological characteristics.

In this context, AI self-efficacy—the belief that one can use AI systems effectively for academic tasks—has emerged as an individual characteristic associated with the academic outcomes of AI use. Wang and Chuang (2024) conceptualized AI self-efficacy as a four-dimensional construct comprising assistance, anthropomorphic interaction, comfort with AI, and technological skills.

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This multidimensional structure suggests that students' perceived competence in different aspects of AI may be associated with academic behavior through distinct statistical pathways. Previous research has shown that AI-related variables—including AI self-efficacy, attitudes toward AI, AI literacy, AI recommendation systems, and AI dependence—are significantly associated with academic procrastination (Hermita et al., 2026; Mukhtar et al., 2025; Shu & Miao, 2021). Although these findings establish a link between individual AI-related characteristics and academic procrastination, explanations of the processes that may account for associations between different dimensions of AI self-efficacy and this behavior remain underdeveloped. Indeed, a study of 1,301 students found that AI self-efficacy mediated the relationship between students' attitudes toward AI and their AI literacy (Asio, 2025).

Self-regulation theory provides a framework for interpreting the relationships between AI self-efficacy and academic procrastination. Self-regulated learning is defined as an active, cyclical process in which individuals set learning goals and plan, monitor, and evaluate their cognitive, motivational, and behavioral processes to achieve those goals (Zimmerman, 2000; Zimmerman & Schunk, 2011). From this theoretical perspective, successful learning requires not only knowledge and skills but also the effective management of these resources. Academic procrastination has therefore long been regarded as a behavioral manifestation of deficiencies in self-regulation (Steel, 2007).

Recent studies examining the relationship between GenAI and self-regulation further support this perspective. GenAI has the potential to support self-regulated learning by providing personalized feedback, just-in-time support, and individualized learning pathways (Aydan, 2026; Banihashem et al., 2025). However, the extent to which this potential translates into educational outcomes varies according to students' self-regulatory skills. Research has shown that lower self-control is associated with more intensive AI use (Rodríguez-Ruiz et al., 2025), self-regulated learning is negatively associated with AI dependence (Liu, 2026), self-control functions as an explanatory mechanism in the relationship between ChatGPT use and academic well-being (Besalti, 2025), and AI dependence decreases as academic self-efficacy and self-control increase (Lu et al., 2026). Taken together, these findings suggest that the educational benefits of AI depend less on the technology itself than on the extent to which students can regulate their learning processes. Thus, AI self-efficacy may be associated with academic procrastination both directly and indirectly through self-regulatory processes that reflect students' capacity to manage their learning. The effects of AI on learning may also depend not only on students' efficacy beliefs regarding AI but also on the extent of their interaction with these tools. AI use frequency is an important behavioral indicator of the degree to which students integrate these technologies into their learning. Recent evidence links the intensity of AI use with self-regulation, self-control, and AI dependence (Liu, 2026; Lu et al., 2026; Rodríguez-Ruiz et al., 2025). Accordingly, the indirect associations between AI self-efficacy and academic procrastination through self-regulatory processes may vary across levels of AI use frequency. Research with pre-service mathematics teachers has also linked ChatGPT use with self-regulated learning and self-efficacy in mathematics learning, with self-regulated learning partially mediating the relationship between ChatGPT use and self-efficacy (Asare & Boateng, 2025).

Nevertheless, the existing literature has three important limitations. First, the associations between the different dimensions of AI self-efficacy and academic procrastination have not been adequately clarified. Second, process-based empirical evidence identifying the self-regulatory processes through which AI self-efficacy is related to academic procrastination remains limited. Third, research has rarely examined whether these self-regulatory mechanisms vary according to students' level of AI use. Consequently, it remains unclear through which self-regulatory mechanisms and under what conditions students' beliefs in their ability to use AI translate into effective learning behavior.

This study aimed to examine the relationships between the assistance, anthropomorphic interaction, comfort with AI, and technological skills dimensions of AI self-efficacy and academic procrastination; test the mediating roles of self-monitoring, self-evaluation, and self-reinforcement;

and determine whether these indirect relationships vary according to AI use frequency. Thus, rather than merely establishing whether AI self-efficacy is associated with academic procrastination, the study sought to explain which self-efficacy dimensions and self-regulatory mechanisms underlie this relationship and how it is shaped by students' frequency of AI use.

Theoretically, this study extends existing explanations of the relationship between AI self-efficacy and academic procrastination by examining the multidimensional structure of AI self-efficacy within self-regulation theory. It also treats AI use frequency as a contextual condition of the self-regulation-based indirect relationship, thereby providing empirical evidence as to whether this mechanism varies with students' level of interaction with AI. Methodologically, the study examines the four dimensions of AI self-efficacy in separate parallel mediation models and tests a corresponding conditional process model for each dimension, irrespective of whether its indirect effects in the initial mediation analysis are statistically significant. Practically, the findings are intended to inform more deliberate design of AI-supported learning environments in higher education and the development of self-regulation-based interventions to reduce academic procrastination.

1.1. AI Self-Efficacy and Academic Procrastination

Self-efficacy beliefs are fundamental cognitive structures that influence how individuals approach academic tasks, how much effort they expend, and how persistent they are when facing difficulties (Bandura, 1997). In AI-supported learning environments, these beliefs encompass students' judgments of their capacity to use AI for academic purposes and integrate it into their learning processes. Wang and Chuang (2024) conceptualized AI self-efficacy as a four-dimensional construct comprising assistance, anthropomorphic interaction, comfort with AI, and technological skills, and showed that it was positively associated with motivated learning behaviors. Because these dimensions represent distinct perceptions of competence in using AI, however, they may influence the initiation and persistence of academic tasks through different functional mechanisms.

The assistance dimension reflects students' confidence in their ability to obtain information and explanations from AI, solve problems, and secure support while completing academic tasks. The capacity of GenAI-supported learning systems to provide structured guidance, address knowledge gaps, and help students manage learning tasks highlights their instructional support function. For example, Hu et al. (2024) found that scaffolding supported by GenAI-based learning companions improved students' information literacy self-efficacy and perceived self-regulated learning. Dai (2025) showed that students use GenAI to generate ideas, compensate for gaps in expertise, support academic discussion, and improve task solutions. Similarly, Pallant et al. (2026) found that using GenAI to address knowledge gaps and structure information was associated with better learning outcomes. Although confidence in obtaining AI assistance may make academic tasks appear more manageable, it does not necessarily imply earlier task initiation. Students may expect to offload cognitively demanding aspects of their work to AI and complete tasks quickly, even when starting close to a deadline. Anticipated assistance may thus serve as a perceived safety net, making postponement seem less risky. Cognitive offloading expectations and the perception of AI assistance as a safety net offer possible explanations for a positive association between assistance self-efficacy and academic procrastination. However, these mechanisms were not directly measured or tested in the present study. Accordingly, assistance self-efficacy was expected to be positively associated with academic procrastination. H1 was therefore formulated as follows.

> H1. The assistance of AI self-efficacy significantly and positively predicts academic procrastination.

The anthropomorphic interaction reflects students' confidence in their ability to communicate naturally with AI, understand the system's responses, and sustain a conversational interaction. Although research directly examining the relationship between this dimension and academic procrastination remains limited, evidence that humanlike AI features influence social presence, trust, attitudes, and learning-related use provides a basis for the proposed relationship. Polyportis and Pahos (2025) showed that perceiving ChatGPT as humanlike strengthened social presence and

attitudes toward the system among university students. Lan et al. (2026) likewise found that AI responsiveness and anthropomorphic features increased students' trust in AI, which in turn was associated with its adoption for learning support, continued interaction, and learning engagement. Students who feel confident interacting with AI effectively and naturally may therefore encounter fewer barriers to seeking support, articulate problems earlier, and overcome interruptions in the task process more readily. Consequently, self-efficacy in anthropomorphic interaction was expected to be associated with lower academic procrastination. H2 was developed on the basis of this theoretical rationale.

H2. The anthropomorphic interaction of AI self-efficacy significantly and negatively predicts academic procrastination.

The comfort with AI encompasses students' perceived competence in using AI tools without difficulty and feeling comfortable while working with them. According to the Technology Acceptance Model, perceived ease of use is a central factor supporting technology adoption and continued use (Davis, 1989). Empirical evidence in the context of GenAI likewise links ease of use to students' trust in AI, perceived usefulness, attitudes, and use behaviors. Pham et al. (2025) found that perceived ease of use significantly increased students' trust in ChatGPT. Alshammari and Babu (2025) showed that ease of use was related to the acceptance processes explaining students' use of ChatGPT and supported continued use through satisfaction. Dai (2025) further identified ease of use as one of the primary determinants of students' decisions about whether to use GenAI. Students who believe they can use AI tools comfortably are likely to spend less time and effort overcoming operational barriers and can therefore direct more attention to the academic task itself. Reduced uncertainty and effort during use may limit technology-related avoidance and delays in task initiation. Feeling comfortable with AI may make students more willing to engage with AI-supported academic tasks. However, ease and confidence in interacting with AI do not necessarily imply that students initiate these tasks promptly or regulate their study time effectively. The rationale presented here therefore does not establish a clear direction for the association between comfort with AI and academic procrastination. Accordingly, the corresponding hypothesis is formulated without specifying a direction.

H3. Comfort with AI is significantly associated with academic procrastination.

The technological skills represent students' confidence in their ability to operate AI tools, formulate appropriate prompts, evaluate system outputs, and use those outputs in ways that align with their learning goals. Access to AI alone does not guarantee effective academic use. Students must also possess the competencies required to use these tools deliberately, critically, and strategically. Shi et al. (2025) found that AI literacy and self-regulated learning positively predicted writing performance among university students. Hu et al. (2024) reported that structured AI support enhanced students' perceptions of self-regulated learning alongside their information literacy self-efficacy. Pallant et al. (2026) further showed that students who used GenAI to structure and elaborate knowledge attained higher levels of learning than those who used it merely to generate ready-made outputs. Although these studies highlight the learning benefits of strategic AI use, they do not directly establish that technological skills self-efficacy is associated with lower academic procrastination. Confidence in operating AI tools and evaluating their outputs is distinct from the self-regulatory capacity to initiate tasks, sustain effort, and meet deadlines. The evidence reviewed therefore provides a basis for examining the association, but not for specifying its direction.

H4. Technological skills self-efficacy is significantly associated with academic procrastination.

The relationship between AI self-efficacy and academic procrastination may depend not only on students' belief that they can use AI but also on their ability to translate that confidence into behaviors that regulate learning. According to self-regulation theory, efficacy beliefs shape academic behavior through mechanisms such as goal setting, strategy selection, monitoring learning, evaluating performance, and adjusting behavior in response to outcomes (Zimmerman,

2000; Zimmerman & Schunk, 2011). Academic procrastination is commonly regarded as a failure of self-regulation between intention and action (Steel, 2007). Empirical studies indicate that self-regulated learning strategies reduce procrastination by supporting student engagement (Zhou & Hiver, 2022) and that self-regulated learning is negatively associated with academic procrastination (García-Ros et al., 2023). Self-efficacy for self-regulation has also been found to play an important role in explaining academic procrastination (Zhang et al., 2018), whereas general self-efficacy is associated with lower levels of academic procrastination (Li et al., 2023).

1.2. Mediating Role of Self-Control and Self-Management Skills

Recent research in the context of GenAI also indicates that self-control and self-regulatory skills are important mechanisms shaping the academic outcomes of AI use. Lower self-control has been associated with more intensive use of AI and greater delegation of tasks to AI (Rodríguez-Ruiz et al., 2025). Self-regulated learning has been shown to reduce AI dependence (Liu, 2026), self-control has emerged as an important mechanism explaining the academic outcomes of AI use (Besalti, 2025); and AI dependence decreases as academic self-efficacy and self-control increase (Lu et al., 2026). Taken together, these findings suggest that the four dimensions of AI self-efficacy may not influence academic procrastination exclusively through direct pathways. Students' beliefs in their ability to obtain assistance from AI, interact with it effectively, use it comfortably, and make use of its technological features may translate into learning behavior through self-monitoring, self-evaluation, and self-reinforcement. The literature provides a rationale for examining indirect associations through self-monitoring, self-evaluation, and self-reinforcement, but does not establish a consistent direction across all four AI self-efficacy dimensions. The mediation analyses are therefore addressed through the following exploratory research question.

RQ 1) What are the directions and magnitudes of the indirect associations between each AI self-efficacy dimension and academic procrastination through self-monitoring, self-evaluation, and self-reinforcement?

1.3. Moderating Role of AI Use Frequency

The translation of self-efficacy beliefs into academic behavior depends not only on individual characteristics but also on individuals' interactions with their learning environment (Bandura, 1997). In the context of GenAI, use frequency is an important behavioral indicator of the extent to which students integrate these technologies into their learning. Recent research suggests that the contribution of AI to self-regulated learning varies with students' level of interaction with AI and that more intensive users display different patterns of self-regulation and learning experience (Lan & Zhou, 2025; Saleh & ElSayary, 2026; Xia et al., 2026). The reviewed literature suggests that indirect associations may differ according to AI use frequency, but does not establish the direction of this variation for each dimension and mediator. The conditional process analyses are therefore addressed through the following exploratory research question.

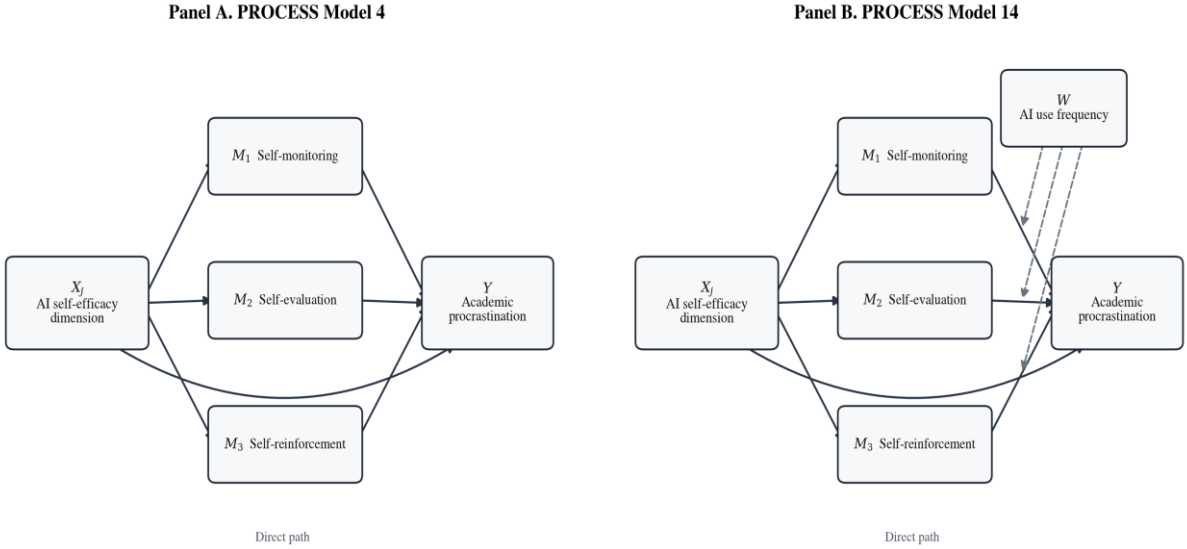
RQ 2) Do the indirect associations between each AI self-efficacy dimension and academic procrastination through self-monitoring, self-evaluation, and self-reinforcement vary with AI use frequency, and, if so, in what direction?

2. Method

2.1. Research Design

This study employed a cross-sectional survey design to examine the relationships of the assistance, anthropomorphic interaction, comfort with AI, and technological skills of AI self-efficacy with academic procrastination; to estimate the indirect effects operating through self-monitoring, self-evaluation, and self-reinforcement; and to determine whether these indirect effects varied as a function of AI use frequency. The study was organized around the two-stage analytical framework presented in Figure 1.

Figure 1
Two-Stage Analytical Framework of the Study



Panel A represents the parallel multiple-mediation structure estimated with PROCESS Model 4 (Hayes, 2018). For each dimension of AI self-efficacy, self-monitoring, self-evaluation, and self-reinforcement were entered simultaneously as parallel mediators, and academic procrastination was specified as the outcome. This stage provided estimates of the specific indirect effect through each mediator while statistically controlling for the other mediators, as well as the total indirect effect obtained by summing the three specific indirect effects.

Panel B extends the same structure using PROCESS Model 14 (Hayes, 2018). AI use frequency was entered as the moderator of the second-stage paths from self-monitoring, self-evaluation, and self-reinforcement to academic procrastination. Thus, the paths from each AI self-efficacy dimension to the mediators were held constant, whereas each mediator-to-outcome path was allowed to vary across levels of AI use frequency. The four analytical models shared this structure and differed only in the focal AI self-efficacy dimension specified as the predictor. Table 1 summarizes the models.

Table 1
Dimension-Specific Analytical Models

Model	*Focal predictor (Xj)*	*Parallel mediators (Mi)*	*Moderator (W)*	*Outcome (Y)*
A	Assistance	Self-monitoring; self-evaluation; self-reinforcement	AI use frequency	Academic procrastination
B	Anthropomorphic interaction	Self-monitoring; self-evaluation; self-reinforcement	AI use frequency	Academic procrastination
C	Comfort with AI	Self-monitoring; self-evaluation; self-reinforcement	AI use frequency	Academic procrastination
D	Technological skills	Self-monitoring; self-evaluation; self-reinforcement	AI use frequency	Academic procrastination

Accordingly, four PROCESS Model 4 analyses and four PROCESS Model 14 analyses were conducted. The conditional process analyses were performed for all four AI self-efficacy dimensions rather than being restricted to dimensions whose unconditional indirect effects were statistically significant in Model 4. For each Model 14 analysis, conditional indirect effects and indices of moderated mediation were estimated separately for self-monitoring, self-evaluation, and self-reinforcement at clearly defined levels of AI use frequency.

2.2. Participants and Procedure

Ethical approval for this study was obtained from Uşak University's Ethics Committee for Scientific Research and Publication in the Social Sciences and Humanities (approval date: September 24, 2026; decision no. 2026/196). Permission to use the measures was obtained from the authors of the relevant development and/or adaptation studies. Data were collected online via Google Forms between May 6 and May 16, 2026, using the measures and a demographic information form. Participants were recruited through convenience sampling from eight undergraduate programs in the Faculty of Education at Uşak University, Türkiye. Eligibility criteria included enrollment in one of these programs during the data-collection period and voluntary provision of informed consent. The introductory page described the study's purpose, stated that responses would be used exclusively for scientific purposes, and explained participants' right to withdraw at any time without penalty. Only those who provided informed consent could access the survey items.

A total of 506 preservice teachers completed the questionnaire. Because the number of eligible students who received the survey invitation could not be established, a response rate could not be calculated. No responses were excluded and no missing data were identified; all 506 responses were therefore included in the analyses. The final sample comprised 506 preservice teachers, including 375 women (74.1%) and 131 men (25.9%). Most participants were between 18 and 23 years of age (89.6%), with the remainder aged 24 or older. The 24–26 age group comprised 37 participants (7.3% of the total sample). Participants were enrolled in Science Education (n = 27, 5.3%), Elementary Mathematics Education (n = 63, 12.5%), Early Childhood Education (n = 52, 10.3%), Special Education (n = 29, 5.7%), Guidance and Psychological Counseling (n = 55, 10.9%), Primary Education (n = 86, 17.0%), Social Studies Education (n = 95, 18.8%), and Turkish Language Education (n = 99, 19.6%).

The sample included 115 first-year students (22.7%), 149 second-year students (29.4%), 128 third-year students (25.3%), and 114 fourth-year students (22.5%). Nearly all participants reported previous experience using AI tools (n = 499, 98.6%), whereas seven participants (1.4%) reported no prior use. Accordingly, the findings primarily reflect the perceptions of preservice teachers who already had some experience with AI.

2.3. Measures

2.3.1. AI self-efficacy

AI self-efficacy was assessed using the AI Self-Efficacy Scale developed by Wang and Chuang (2024) and adapted into Turkish by Güney and Semerci Şahin (2026). The scale comprises four dimensions: assistance (7 items), anthropomorphic interaction (5 items), comfort with AI (6 items), and technological skills (4 items). The original development study reported that the four-factor structure was supported by exploratory and confirmatory factor analyses and provided strong evidence of construct validity (Wang & Chuang, 2024). Confirmatory factor analysis yielded χ^2 = 580.876, df = 200, and χ^2/df = 2.904. The fit indices (RMSEA = .082, GFI = .846, RFI = .870, IFI = .926, CFI = .925, and NFI = .891) indicated an acceptable model fit. In the present study, Cronbach's alpha coefficients were .91 for assistance, .93 for anthropomorphic interaction, .93 for comfort with AI, and .81 for technological skills.

2.3.2. Self-control and self-management skills

Self-control and self-management were assessed using the Self-Control and Self-Management Scale developed by Mezo (2009) and adapted into Turkish by Ercoşkun (2016). The scale comprises three dimensions: self-monitoring (6 items), self-evaluation (5 items), and self-reinforcement (5 items). These general self-control and self-management skills were examined in an academic context but do not represent the full scope of self-regulated learning, which also encompasses cognitive, motivational, and affective processes (Panadero, 2017). Confirmatory factor analysis in the Turkish adaptation study showed that the second-order three-factor model fit the data well. The reported fit indices were RMSEA = .052, NFI = .97, CFI = .98, GFI = .96, AGFI = .94, and RFI = .97 (Ercoşkun,

2016). The Turkish adaptation study reported Cronbach's alpha coefficients of .82, .73, and .74 for self-monitoring, self-evaluation, and self-reinforcement, respectively. In the present study, the corresponding coefficients were .88, .83, and .81.

2.3.3. Academic procrastination

The Academic Procrastination Scale–Short Form, developed by McCloskey (2011) and Yockey (2016) and adapted into Turkish by Balkıs and Duru (2022), is a unidimensional five-item scale rated from 1 ("Strongly disagree") to 5 ("Strongly agree"). Confirmatory factor analysis showed that the model fit the data excellently [$\chi^2(5, N = 272) = 7.253$, $p = .20$; $\chi^2/\mathrm{df} = 1.453$; RMSEA = .04, 90% CI [.00, .10]; SRMR = .02; GFI = .99; CFI = 1.00; TLI = .99; NFI = .99; RFI = .98]. The Turkish adaptation study reported a Cronbach's alpha internal-consistency coefficient of .87. In the present study, Cronbach's alpha was .90.

2.3.4. AI use frequency

AI use frequency was assessed using a single item: "How often do you use AI tools?" Responses were coded as 0 = never, 1 = rarely, 2 = a few times a month, 3 = a few times a week, and 4 = every day, with higher scores indicating more frequent AI use. No specific recall period was specified. Participants reported their general frequency of AI tool use. Although the response categories were ordinal, the coded score was treated as a continuous moderator in the PROCESS analyses, assuming equal spacing between adjacent categories and a linear moderation relationship. The score was mean-centered before constructing the interaction terms. This measure was distinct from prior AI use, which recorded whether participants had ever used AI tools. Prior AI use was reported descriptively, whereas AI use frequency served as the moderator in the conditional process models. The response distribution was as follows: never, $n = 4$ (0.8%); rarely, $n = 25$ (4.9%); a few times a month, $n = 47$ (9.3%); a few times a week, $n = 249$ (49.2%); and every day, $n = 181$ (35.8%). Neither AI use frequency nor technological self-efficacy should be interpreted as a comprehensive measure of AI literacy, which also includes evaluative and ethical dimensions (Ng et al., 2021).

2.4. Data Analysis

Before analysis, the data were examined for missing observations, distributional properties, and potential outliers. After the pattern of missing data had been evaluated, analyses were conducted with participants who had complete data on the relevant variables. Univariate and multivariate outliers were assessed using standardized and deleted studentized residuals, Mahalanobis distance, leverage, and Cook's distance. These indicators were considered jointly to determine not only whether observations were unusual but also whether they exerted undue influence on the regression coefficients (Cook, 1977).

Post hoc influential-case sensitivity analyses were conducted for the separate and joint models. Diagnostic screening used absolute externally studentized residuals greater than 3, leverage greater than $2(k + 1)/N$, and Cook's distance greater than $4/N$, where k denotes the number of predictors excluding the intercept. Mahalanobis distances were also examined descriptively. For the sensitivity comparisons, observations exceeding the Cook's distance threshold in any mediator or outcome equation were temporarily omitted from the corresponding model. Full-sample and screened-sample models were estimated using OLS, HC3 standard errors, and 5,000 percentile bootstrap resamples. The parallel mediation comparisons therefore assessed the OLS counterparts of the models rather than directly repeating the reliability-corrected EIV analyses. These checks did not alter the primary analytical sample.

The distributional properties of the variables were evaluated using skewness and kurtosis coefficients, while the approximate normality of the residuals was assessed with a histogram and a normal P–P plot. Linearity and homoscedasticity were examined in a scatterplot of standardized residuals against standardized predicted values. The Durbin–Watson statistic was 1.966. However, this statistic does not establish independence among participants sharing the same academic program or class. VIF and tolerance values were interpreted as diagnostic indicators of the extent

to which shared variance among predictors affected coefficient estimates, rather than as rigid thresholds (O'Brien, 2007).

The study variables were described using means and standard deviations, and bivariate linear relationships among them were examined using Pearson product–moment correlation coefficients. Pearson's correlation coefficient permits assessment of the direction and magnitude of the linear relationship between continuous variables (Schober et al., 2018).

The indirect relationships specified in the theoretical model were tested using parallel mediation analysis with Model 4 in Hayes's PROCESS macro. Each AI self-efficacy dimension was modeled as a separate independent variable; academic procrastination was the dependent variable; and self-monitoring, self-evaluation, and self-reinforcement were entered simultaneously as mediators. This approach enabled estimation of the total indirect effect as well as each specific indirect effect while controlling for the other mediators (Preacher & Hayes, 2008). The Model 4 analyses used errors-in-variables regression incorporating reliability estimates for the predictor and mediator scores. The reliability values entered were .91 for assistance, .93 for anthropomorphic interaction, .93 for comfort with AI, and .81 for technological skills; the corresponding values for self-monitoring, self-evaluation, and self-reinforcement were .88, .83, and .81, respectively. In addition to the primary mediation analyses, AI use frequency was included as a moderator and conditional process analysis was performed using PROCESS Model 14 to examine whether the proposed model operated similarly across different levels of AI use. For each of the four AI self-efficacy dimensions, PROCESS Model 14 was used to estimate conditional indirect associations through self-monitoring, self-evaluation, and self-reinforcement, with AI use frequency specified as the moderator of each mediator–outcome relationship (Hayes, 2018). The Model 14 analyses used ordinary least squares estimation with HC3 standard errors and did not incorporate the reliability-based measurement error correction used in Model 4. Conditional indirect effects were evaluated at the 16th, 50th, and 84th percentiles of AI use frequency. The corresponding observed scores were 3, 3, and 4, representing use a few times a week at the 16th and 50th percentiles and daily use at the 84th percentile. After subtracting the sample mean of 3.1423, these values were −0.1423, −0.1423, and 0.8577, respectively. Because the 16th and 50th percentiles coincided, results are reported at two distinct evaluation points: use a few times a week and daily use. References to lower and higher frequency denote these relative evaluation points, not groups created by splitting the sample.

Johnson–Neyman regions were not reported because AI use frequency comprised five ordered response categories, making thresholds between category codes difficult to interpret substantively. Although the coded score was treated as continuous in the regression models, probing was restricted to the observed response values represented by the selected percentiles. Moderated mediation was evaluated using bootstrap confidence intervals for the indices of moderated mediation, rather than inferred from the significance of conditional mediator–outcome associations (Hayes, 2015).

The mediation and conditional process analyses were conducted using PROCESS version 5.0. For the Model 14 analyses, indirect associations and indices of moderated mediation were evaluated using 95% percentile bootstrap confidence intervals based on 5,000 resamples. Statistical significance was evaluated using 95% bootstrap confidence intervals, and an indirect effect was considered statistically significant when its confidence interval did not include zero (Hayes & Scharkow, 2013). The significance level for all statistical tests was set at $p < .05$. HC3 heteroskedasticity-consistent standard errors were used for the regression coefficients in both PROCESS Model 4 and Model 14. The corresponding coefficient tests and 95% confidence intervals were based on HC3 standard errors, whereas inference for indirect associations and indices of moderated mediation was based on bootstrap confidence intervals. All regression coefficients and total, direct, indirect, and conditional indirect effect estimates are reported in unstandardized form and denoted by b. Variables were not standardized to z scores before analysis. For the moderation analyses, the mediators and AI use frequency were mean-centered. This procedure retained their original measurement units. Because internal consistency alone does not establish construct

validity, measurement quality was evaluated beyond Cronbach's alpha (Flake et al., 2017).

An eight-factor confirmatory factor analysis was conducted in Python using semopy to evaluate the measurement model in the current sample. Item responses were treated as approximately continuous and analyzed using maximum likelihood estimation. Parameter standard errors were estimated using a sandwich estimator, whereas global fit indices were conventional, unscaled ML statistics. Measurement quality was evaluated using standardized factor loadings, factor correlations, composite reliability, average variance extracted (AVE), and the heterotrait–monotrait ratio (HTMT).

Robustness analyses were conducted in Python using statsmodels and NumPy, with all four AI self-efficacy dimensions entered simultaneously into each mediator and outcome equation. The parallel mediation and second-stage moderated mediation specifications were estimated using ordinary least squares, HC3 standard errors, and 95% percentile bootstrap confidence intervals based on 5,000 participant-level resamples. These analyses did not apply the reliability-based errors-in-variables correction used in the primary Model 4 analyses. Corresponding separate OLS models were also estimated to distinguish changes associated with joint adjustment from differences in estimation method. The adjusted associations were interpreted as exploratory and did not establish causal relationships or differences in association strength between dimensions.

The four conditional process models yielded 12 mediator-specific interaction tests and 12 indices of moderated mediation. The reported p values and 95% bootstrap confidence intervals were not adjusted for multiple testing and therefore do not provide familywise error control across these pathways. Statistically significant results are consequently interpreted as exploratory evidence requiring replication rather than definitive confirmation of moderated mediation.

A sensitivity analysis based on the noncentral F distribution indicated that, with $N = 506$, eight predictors in the outcome equation, and one interaction term tested at $\alpha = .05$, an incremental effect of approximately $f^2 = .0156$ could be detected with 80% power. This calculation assumes a conventional fixed-model regression with normally distributed, homoskedastic errors and provides an approximate sensitivity benchmark rather than a direct assessment of power for the HC3 tests or bootstrap indices of moderated mediation.

The initial negative expectations for comfort with AI and technological skills were not supported. Their nondirectional formulations and the questions concerning indirect and conditional indirect associations are treated as exploratory rather than a priori predictions. Cognitive offloading and safety-net perceptions are considered possible explanations; these mechanisms were not directly measured or tested.

3. Results

3.1. Preliminary Analyses and Regression Assumptions

Before the mediation analyses, the distributional properties of the variables and the regression assumptions were examined. Skewness coefficients ranged from −.927 to .306 and kurtosis coefficients from −.752 to 2.430. Particularly in view of the sample size, these values indicated no severe distributional departures that would preclude mediation analysis.

The residual histogram was approximately symmetric and bell-shaped, and observations in the normal P–P plot largely followed the diagonal line. The scatterplot of standardized residuals against standardized predicted values displayed no pronounced curvilinear or funnel-shaped pattern. These findings indicated that the residuals were approximately normally distributed and that the assumptions of linearity and homoscedasticity were met to an acceptable degree. Joint evaluation of the residual histogram, normal probability plot, and residual-versus-predicted scatterplot is consistent with recommended regression diagnostic practice.

Independence of residuals was assessed using the Durbin–Watson statistic, which was very close to 2 (DW = 1.966). Tolerance values ranged from .407 to .810 and VIF values from 1.235 to 2.455, indicating no multicollinearity severe enough to distort coefficient estimates. The joint use of the Durbin–Watson statistic, tolerance, and VIF to evaluate regression assumptions is consistent with established practice in the literature.

Standardized residuals ranged from −2.587 to 3.194, with only one observation exceeding ±3. The maximum Mahalanobis distance was 48.425 and the maximum leverage value was .096; several observations were therefore examined further as potential multivariate outliers. The maximum Cook's distance was .095. This value alone does not establish that the estimates were unaffected by influential observations. Their influence requires evaluation through sensitivity analyses comparing the full-sample results with results obtained after excluding flagged cases. Joint consideration of standardized residuals, Mahalanobis distance, leverage, and Cook's distance represents the recommended diagnostic approach for identifying potential outlying and influential observations.

Overall, the preliminary analyses revealed no major violations of normality, linearity, homoscedasticity, or multicollinearity that would preclude regression-based mediation analyses.

3.2. Descriptive Statistics and Relationships among the Variables

Table 2 presents descriptive statistics and Pearson correlation coefficients for the study variables. Positive and significant correlations were observed among the dimensions of AI self-efficacy. These correlations ranged from small to moderately strong, with the strongest association occurring between anthropomorphic interaction and comfort with AI (r = .628, p < .01). The correlations between comfort with AI and technological skills (r = .578, p < .01) and between assistance and comfort with AI (r = .517, p < .01) were also relatively strong.

The self-control and self-management dimensions were positively intercorrelated. The strongest association was between self-monitoring and self-reinforcement (r = .456, p < .01). The correlations between self-monitoring and self-evaluation (r = .316, p < .01) and between self-evaluation and self-reinforcement (r = .266, p < .01) were small to moderate.

Academic procrastination was negatively associated with self-monitoring (r = −.277, p < .01), self-evaluation (r = −.352, p < .01), and self-reinforcement (r = −.120, p < .01). Of these variables, self-evaluation exhibited the strongest association with academic procrastination. Higher self-control and self-management scores were associated with lower academic procrastination scores.

The assistance (r = .135, p < .01), comfort with AI (r = .146, p < .01), and technological skills (r = .176, p < .01) dimensions of AI self-efficacy showed small positive correlations with academic procrastination. The correlation between anthropomorphic interaction and academic procrastination was not significant (r = .077, p > .05).

Relationships between the AI self-efficacy dimensions and the self-control and self-management dimensions also varied. Assistance was positively associated with self-monitoring (r = .165, p < .01), self-evaluation (r = .146, p < .01), and self-reinforcement (r = .193, p < .01). Anthropomorphic interaction was not significantly associated with self-monitoring (r = −.082, p > .05) or self-reinforcement (r = −.032, p > .05), but it was negatively associated with self-evaluation (r = −.245, p < .01). Comfort with AI showed only a small positive correlation with self-reinforcement (r = .094, p < .05). Technological skills were not significantly associated with any of the self-control and self-management dimensions (p > .05).

AI use frequency was positively correlated with assistance self-efficacy (r = .267, p < .001), comfort with AI (r = .152, p < .001), technological skills (r = .096, p = .031), and self-reinforcement (r = .129, p = .004). Its correlations with anthropomorphic interaction, self-monitoring, self-evaluation, and academic procrastination were not statistically significant (p > .05).

An eight-factor measurement model was evaluated in the current sample to examine the measurement properties of the study constructs. Table 3 summarizes the standardized factor loading ranges, composite reliability, and average variance extracted, with global model fit indices reported in the table note. The eight-factor measurement model showed mixed fit. Composite reliability ranged from .815 to .933, whereas AVE ranged from .492 to .731. Self-evaluation had marginal AVE, and one self-reinforcement item had a low standardized loading (.291). The largest absolute factor correlation was .663, and the highest HTMT value was .674, providing evidence of construct differentiation despite the limitations in overall fit.

Table 2

Descriptive Statistics and Pearson Correlations among the Variables

Variable	*N*	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1. Assistance	506	5.61	1.03	—								
2. Anthropomorphic interaction	506	3.58	1.54	.231**	—							
3. Comfort with AI	506	4.37	1.42	.517**	.628**	—						
4. Technological skills	506	4.29	1.38	.422**	.416**	.578**	—					
5. Self-monitoring	506	3.49	0.81	.165**	−.082	.003	.019	—				
6. Self-evaluation	506	3.28	1.05	.146**	−.245**	−.078	−.086	.316**	—			
7. Self-reinforcement	506	3.49	0.84	.193**	−.032	.094*	.061	.456**	.266**	—		
8. Academic procrastination	506	2.77	1.05	.135**	.077	.146**	.176**	−.277**	−.352**	−.120**	—	
9. AI use frequency	506	3.14	0.84	.267**	.001	.152**	.096*	.056	.062	.129**	.074	—

Note. $N = 506$. *$p < .05$. **$p < .01$. AI use frequency was coded from 0 (never) to 4 (every day). Correlations were calculated using the original, uncentered scores. All tests were two-tailed, and p values were not adjusted for multiple testing.

Table 3

Measurement Properties of the Study Constructs

Construct	*Standardized loading range*	*CR*	*AVE*
Assistance	.597–.879	.912	.599
Anthropomorphic interaction	.802–.887	.931	.731
Comfort with AI	.621–.943	.933	.701
Technological skills	.614–.781	.815	.527
Self-monitoring	.681–.828	.879	.549
Self-evaluation	.564–.769	.827	.492
Self-reinforcement	.291–.854	.838	.529
Academic procrastination	.722–.864	.896	.634

Note. CR = composite reliability; AVE = average variance extracted. Eight-factor model fit: $\chi^2(832) = 2221.13$, $p < .001$; CFI = .903; TLI = .895; RMSEA = .057, 90% CI [.055, .060]; SRMR = .058. Fit statistics are conventional, unscaled ML estimates.

3.3. Mediation Results

Four parallel mediation models were estimated, with each dimension of AI self-efficacy entered separately as the independent variable and self-monitoring, self-evaluation, and self-reinforcement entered as parallel mediators. Table 4 provides a comparative summary of the total and direct effects, the mediator-specific indirect effects, and the resulting mediation patterns across the four models. The model-specific findings presented after the table elaborate the individual paths underlying these effects.

Table 4
Total, direct, and indirect effects of AI self-efficacy dimensions on academic procrastination

AI self-efficacy dimension (X)	*Total effect, b [95% CI]*	*Direct effect, b [95% CI]*	*Indirect effect via self-monitoring, b [95% BootCI]*	*Indirect effect via self-evaluation, b [95% BootCI]*	*Indirect effect via self-reinforcement, b [95% BootCI]*	*Mediation pattern*
Assistance	**0.151**** [0.047, 0.255]	**0.248***** [0.152, 0.343]	**−0.047** [−0.097, −0.012]	**−0.064** [−0.111, −0.022]	0.014 [−0.013, 0.049]	Inconsistent mediation
Anthropomorphic interaction	0.057 [−0.013, 0.126]	−0.023 [−0.092, 0.046]	0.014 [−0.004, 0.038]	**0.068** [0.035, 0.109]	−0.003 [−0.015, 0.006]	Indirect-only mediation
Comfort with AI	**0.117**** [0.041, 0.192]	**0.089*** [0.016, 0.163]	−0.001 [−0.023, 0.021]	0.022 [−0.006, 0.053]	0.006 [−0.004, 0.023]	Direct-only non-mediation
AI-related technological skills	**0.167***** [0.080, 0.253]	**0.138**** [0.056, 0.221]	−0.004 [−0.031, 0.021]	0.028 [−0.006, 0.065]	0.005 [−0.005, 0.019]	Direct-only non-mediation

Note. The dependent variable was academic procrastination. b = unstandardized effect coefficient; CI = confidence interval; BootCI = bootstrap confidence interval. Confidence intervals for the total and direct effects were based on HC3 heteroskedasticity-consistent standard errors. Indirect effects were estimated using 5,000 bootstrap samples and were considered significant when their bootstrap confidence intervals did not include zero. $p < .05$. $p < .01$. $p < .001$.

3.3.1. Mediation Results of Model A

As summarized in Table 4, the assistance model produced significant indirect effects through self-monitoring and self-evaluation, whereas the indirect effect through self-reinforcement was not significant.

The mediation analysis showed that the assistance dimension significantly and positively predicted self-monitoring (b = 0.143, SE = 0.049, 95% CI [0.047, 0.238]). Self-monitoring, in turn, had a significant negative effect on academic procrastination (b = −0.328, SE = 0.090, 95% CI [−0.504, −0.151]). Self-monitoring was a significant mediator of the effect of the assistance dimension on academic procrastination (b = −0.047, SE = 0.021, 95% CI [−0.097, −0.012]).

The assistance dimension also significantly and positively predicted self-evaluation (b = 0.163, SE = 0.052, 95% CI [0.060, 0.266]). Self-evaluation had a significant negative effect on academic procrastination (b = −0.392, SE = 0.061, 95% CI [−0.513, −0.272]). These results showed that self-evaluation was also a significant mediator of the relationship between the assistance dimension and academic procrastination (b = −0.064, SE = 0.023, 95% CI [−0.111, −0.022]).

The assistance dimension significantly and positively predicted self-reinforcement (b = 0.171, SE = 0.043, 95% CI [0.086, 0.256]). However, self-reinforcement did not have a significant effect on academic procrastination (b = 0.081, SE = 0.086, 95% CI [−0.088, 0.250]). Accordingly, self-reinforcement did not significantly mediate the relationship between the assistance dimension and academic procrastination (b = 0.014, SE = 0.015, 95% CI [−0.013, 0.049]).

Finally, the total effect of the assistance dimension on academic procrastination was positive and significant (b = 0.151, SE = 0.053, 95% CI [0.047, 0.255]). After the mediators were included in the model, the direct effect also remained positive and significant (b = 0.248, SE = 0.049, 95% CI [0.152, 0.343]). The total indirect effect through the three mediators was significant and negative (b = −0.097, SE = 0.030, 95% CI [−0.159, −0.039]). Thus, assistance self-efficacy showed a positive direct association with academic procrastination and negative indirect associations through self-monitoring and self-evaluation. Self-reinforcement, by contrast, did not play a significant mediating role. The model therefore displayed a competitive (inconsistent) mediation pattern, with the direct and indirect effects operating in opposite directions.

3.3.2. Mediation Results of Model B

As shown in Table 4, anthropomorphic interaction was associated with academic procrastination indirectly only through self-evaluation.

The mediation analysis showed that the anthropomorphic interaction dimension significantly and negatively predicted self-evaluation (b = −0.179, SE = 0.038, 95% CI [−0.253, −0.106]). Self-evaluation was also significantly and negatively associated with academic procrastination (b = −0.379, SE = 0.065, 95% CI [−0.506, −0.252]). Self-evaluation was a significant mediator of the effect of anthropomorphic interaction on academic procrastination (b = 0.068, SE = 0.019, 95% CI [0.035, 0.109]).

However, anthropomorphic interaction did not have a significant effect on self-monitoring (b = −0.046, SE = 0.031, 95% CI [−0.107, 0.014]). Consistent with this result, self-monitoring did not mediate the relationship between anthropomorphic interaction and academic procrastination (b = 0.014, SE = 0.011, 95% CI [−0.004, 0.038]).

Similarly, anthropomorphic interaction did not have a significant effect on self-reinforcement (b = −0.019, SE = 0.029, 95% CI [−0.075, 0.038]). Self-reinforcement also did not significantly predict academic procrastination (b = 0.136, SE = 0.086, 95% CI [−0.033, 0.306]). Consequently, self-reinforcement was not a significant mediator of the relationship between anthropomorphic interaction and academic procrastination (b = −0.003, SE = 0.005, 95% CI [−0.015, 0.006]).

Finally, the total effect of anthropomorphic interaction on academic procrastination was not significant (b = 0.057, SE = 0.035, 95% CI [−0.013, 0.126]). Likewise, the direct effect remained nonsignificant after the mediators were included (b = −0.023, SE = 0.035, 95% CI [−0.092, 0.046]). In contrast, the total indirect effect through the three mediators was significant (b = 0.080, SE = 0.021, 95% CI [0.041, 0.124]). A significant indirect association between anthropomorphic interaction and academic procrastination was found only through self-evaluation; the indirect associations through self-monitoring and self-reinforcement were nonsignificant.

3.3.3. Mediation Results of Model C

As summarized in Table 4, none of the three mediator-specific indirect effects was significant in the comfort-with-AI model.

The mediation analysis showed that comfort with AI significantly and positively predicted self-reinforcement (b = 0.060, SE = 0.029, 95% CI [0.002, 0.117]). However, self-reinforcement did not have a significant effect on academic procrastination (b = 0.105, SE = 0.088, 95% CI [−0.067, 0.277]) and was not a significant mediator of the relationship between comfort with AI and academic procrastination (b = 0.006, SE = 0.007, 95% CI [−0.004, 0.023]).

Comfort with AI did not significantly affect self-monitoring (b = 0.002, SE = 0.034, 95% CI [−0.065, 0.069]). Similarly, self-monitoring did not significantly mediate the relationship between comfort with AI and academic procrastination (b = −0.001, SE = 0.011, 95% CI [−0.023, 0.021]).

Comfort with AI also did not significantly affect self-evaluation (b = −0.062, SE = 0.040, 95% CI [−0.140, 0.016]). Accordingly, self-evaluation was not a significant mediator of the relationship between comfort with AI and academic procrastination (b = 0.022, SE = 0.015, 95% CI [−0.006, 0.053]).

Finally, the total effect of comfort with AI on academic procrastination was positive and significant (b = 0.117, SE = 0.038, 95% CI [0.041, 0.192]). After the mediators were included, the direct effect also remained positive and significant (b = 0.089, SE = 0.037, 95% CI [0.016, 0.163]). In contrast, the total indirect effect through the three mediators was not significant (b = 0.028, SE = 0.020, 95% CI [−0.011, 0.067]). Thus, self-monitoring, self-evaluation, and self-reinforcement did not significantly mediate the relationship between comfort with AI and academic procrastination.

3.3.4. Mediation Results of Model D

As shown in Table 4, the technological-skills model exhibited a direct-only, non-mediation pattern.

The mediation analysis showed that AI-related technological skills did not have a significant effect on self-monitoring (b = 0.014, SE = 0.040, 95% CI [−0.064, 0.092]). Self-monitoring had a

significant negative effect on academic procrastination (b = −0.311, SE = 0.089, 95% CI [−0.485, −0.136]); however, it did not significantly mediate the relationship between technological skills and academic procrastination (b = −0.004, SE = 0.013, 95% CI [−0.031, 0.021]).

Similarly, technological skills did not have a significant effect on self-evaluation (b = −0.081, SE = 0.050, 95% CI [−0.180, 0.018]). Self-evaluation, in contrast, had a significant negative effect on academic procrastination (b = −0.342, SE = 0.063, 95% CI [−0.466, −0.219]). Nevertheless, self-evaluation was not a significant mediator of the relationship between technological skills and academic procrastination (b = 0.028, SE = 0.018, 95% CI [−0.006, 0.065]).

Technological skills also did not have a significant effect on self-reinforcement (b = 0.046, SE = 0.036, 95% CI [−0.026, 0.117]). The effect of self-reinforcement on academic procrastination was likewise nonsignificant (b = 0.107, SE = 0.088, 95% CI [−0.065, 0.279]). Accordingly, self-reinforcement did not significantly mediate the relationship between technological skills and academic procrastination (b = 0.005, SE = 0.006, 95% CI [−0.005, 0.019]).

Finally, the total effect of technological skills on academic procrastination was positive and significant (b = 0.167, SE = 0.044, 95% CI [0.080, 0.253]). After the mediators were included, the direct effect also remained positive and significant (b = 0.138, SE = 0.042, 95% CI [0.056, 0.221]). In contrast, the total indirect effect through self-monitoring, self-evaluation, and self-reinforcement was not significant (b = 0.028, SE = 0.024, 95% CI [−0.019, 0.076]). These results show that AI-related technological skills directly and positively predicted academic procrastination, but this relationship was not explained by self-monitoring, self-evaluation, or self-reinforcement. The model therefore exhibited a direct-only, non-mediation pattern.

3.4. Moderated Mediation Analyses

Four second-stage moderated mediation analyses were conducted using PROCESS Model 14 to determine whether AI use frequency moderated the indirect relationships between the four dimensions of AI self-efficacy and academic procrastination. In each model, self-monitoring, self-evaluation, and self-reinforcement were entered as parallel mediators, and AI use frequency was specified as the moderator of the relationships between these mediators and academic procrastination. Table 5 presents the 12 mediators × AI use frequency interaction effects estimated across the four models.

Table 5

Moderated Mediation Results for the Four Conditional Process Models

X	M_i	$M_i \times W$, *b*	*SE (HC3)*	*t*	*p*	*%95 CI [LL, UL]*	ΔR^2	R^2	*Adjusted* R^2
Assistance	M_1	−0.0405	0.0748	−0.5419	.5881	[−0.1876, 0.1065]	.0005	.2103	.1976
Assistance	M_2	0.0917	0.0414	2.2137	.0273	[0.0103, 0.1731]	.0078		
Assistance	M_3	0.0503	0.0708	0.7103	.4779	[−0.0888, 0.1893]	.0009		
Anthropomorphic interaction	M_1	−0.0500	0.0723	−0.6909	.4899	[−0.1920, 0.0921]	.0008	.1787	.1655
Anthropomorphic interaction	M_2	0.1093	0.0438	2.4963	.0129	[0.0233, 0.1953]	.0112		
Anthropomorphic interaction	M_3	0.0763	0.0731	1.0436	.2972	[−0.0673, 0.2199]	.0020		
Comfort with AI	M_1	−0.0648	0.0723	−0.8960	.3707	[−0.2068, 0.0773]	.0014	.1882	.1751
Comfort with AI	M_2	0.0999	0.0417	2.3971	.0169	[0.0180, 0.1819]	.0093		
Comfort with AI	M_3	0.0761	0.0715	1.0642	.2878	[−0.0644, 0.2167]	.0020		
Technological skills	M_1	−0.0579	0.0703	−0.8242	.4102	[−0.1960, 0.0802]	.0011	.1974	.1845
Technological skills	M_2	0.1000	0.0406	2.4652	.0140	[0.0203, 0.1797]	.0094		
Technological skills	M_3	0.0731	0.0697	1.0493	.2946	[−0.0638, 0.2101]	.0018		

Note. N = 506. Academic procrastination (Y) is the dependent variable, and AI use frequency (W) is the moderator in all models. X denotes the corresponding dimension of AI self-efficacy. M_1 = self-monitoring; M_2 = self-evaluation; M_3 = self-reinforcement. $M_i \times W$ denotes the interaction between the corresponding mediator and AI use frequency. b = unstandardized regression coefficient; SE (HC3) = HC3 heteroskedasticity-consistent standard error; CI = confidence interval; LL = lower limit; UL = upper limit. ΔR^2 indicates the unique increment in explained variance associated with each interaction term, conditional on the other terms in the outcome model. The mediators and moderator were mean-centered before analysis. Standard errors, significance tests, and 95% confidence intervals for the interaction coefficients are based on the HC3 estimator. All tests are two-tailed; interactions were considered statistically significant when $p < .05$ and the 95% confidence interval excluded zero.

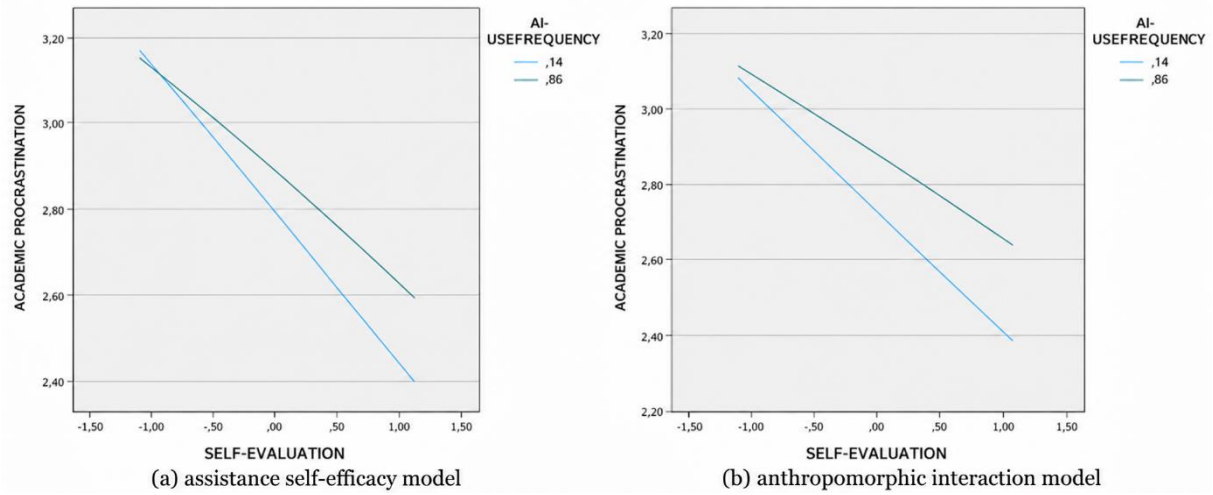
As shown in Table 5, AI use frequency consistently moderated the relationship between self-evaluation and academic procrastination. The self-evaluation × AI use frequency interaction was positive and significant in the assistance (b = 0.0917, SE = 0.0414, t = 2.2137, p = .0273, 95% CI [0.0103, 0.1731]), anthropomorphic interaction (b = 0.1093, SE = 0.0438, t = 2.4963, p = .0129, 95% CI [0.0233, 0.1953]), comfort-with-AI (b = 0.0999, SE = 0.0417, t = 2.3971, p = .0169, 95% CI [0.0180, 0.1819]), and technological-skills models (b = 0.1000, SE = 0.0406, t = 2.4652, p = .0140, 95% CI [0.0203, 0.1797]). The positive interaction coefficients indicate that the negative association between self-evaluation and academic procrastination was smaller in magnitude at higher levels of AI use frequency. In contrast, the self-monitoring × AI use frequency and self-reinforcement × AI use frequency interactions were nonsignificant in all four models. As illustrated in Figure 2, the negative association between self-evaluation and academic procrastination was stronger at lower levels of AI use frequency and weaker at higher levels, as indicated by the steeper negative slopes for less frequent AI users.

A significant mediator × moderator interaction, however, does not necessarily indicate that the corresponding indirect effect is moderated. This conclusion depends on whether the bootstrap confidence interval for the index of moderated mediation excludes zero. For the assistance model, the index of moderated mediation through self-evaluation excluded zero under the unadjusted 95% bootstrap criterion (index = 0.0136, BootSE = 0.0079, 95% bootstrap CI [0.0016, 0.0325]). The negative indirect association was larger in absolute magnitude at use a few times a week (b = −0.0472, 95% bootstrap CI [−0.0814, −0.0171]) than at daily use (b = −0.0336, 95% bootstrap CI [−0.0655, −0.0082]). The indices through self-monitoring (index = −0.0053, 95% bootstrap CI [−0.0256, 0.0157]) and self-reinforcement (index = 0.0078, 95% bootstrap CI [−0.0145, 0.0317]) included zero.

For anthropomorphic interaction, the index of moderated mediation through self-evaluation was negative and excluded zero under the unadjusted 95% bootstrap criterion (index = −0.0182, BootSE = 0.0081, 95% bootstrap CI [−0.0358, −0.0041]). The positive indirect association was larger at use a few times a week (b = 0.0518, 95% bootstrap CI [0.0277, 0.0811]) than at daily use (b = 0.0336, 95% bootstrap CI [0.0076, 0.0646]). The indices through self-monitoring (index = 0.0022, 95% bootstrap CI [−0.0055, 0.0112]) and self-reinforcement (index = −0.0013, 95% bootstrap CI [−0.0081, 0.0043]) included zero.

Figure 2

Moderating effect of AI use frequency on the relationship between self-evaluation and academic procrastination: (a) assistance self-efficacy model and (b) anthropomorphic interaction model



(a) assistance self-efficacy model (b) anthropomorphic interaction model

Although the self-evaluation × AI use frequency interaction was significant in the comfort-with-AI and technological-skills models, their corresponding indices of moderated mediation were not significant. The bootstrap confidence intervals included zero for both comfort with AI (index = −0.0058, BootSE = 0.0046, 95% bootstrap CI [−0.0169, 0.0011]) and technological skills (index =

−0.0066, BootSE = 0.0050, 95% bootstrap CI [−0.0181, 0.0011]). This distinction indicates that AI use frequency moderated the self-evaluation–academic procrastination path in all four models, but statistically significant indices of moderated mediation were found only in the assistance and anthropomorphic interaction models. Under the reported inferential criteria, H1 was supported, whereas H2 was not supported. The negative associations initially expected for comfort with AI and technological skills were not supported; the nondirectional associations addressed by H3 and H4 were examined on an exploratory basis. The observed positive associations should therefore not be interpreted as confirmation of the initial negative expectations. Regarding RQ1, the assistance model showed negative indirect associations through self-monitoring and self-evaluation, whereas anthropomorphic interaction showed a positive indirect association through self-evaluation. Regarding RQ2, the unadjusted 95% bootstrap confidence intervals for the indices of moderated mediation excluded zero only for the self-evaluation pathways in the assistance and anthropomorphic interaction models. These conditional process findings remain exploratory because the inferences were not adjusted for multiple testing.

Robustness analyses jointly included all four AI self-efficacy dimensions. Assistance retained its positive direct association and negative indirect associations through self-monitoring and self-evaluation. Anthropomorphic interaction retained its positive indirect association through self-evaluation, but its adjusted direct association became negative. The direct associations for comfort with AI and technological skills were no longer statistically significant. In the adjusted conditional process model, the self-evaluation indices of moderated mediation excluded zero for assistance (index = .0223, 95% bootstrap CI [.0028, .0485]) and anthropomorphic interaction (index = −.0181, CI [−.0367, −.0024]); all remaining indices included zero. These findings remain exploratory because inference was not adjusted for multiple testing. Full results are provided in the supplementary material.

Influential-case screening retained 421–446 participants in the separate conditional process models and 423 in the joint model. The conditional indirect associations through self-evaluation remained negative for assistance and positive for anthropomorphic interaction at both weekly and daily AI use. However, the bootstrap confidence intervals for their indices of moderated mediation included zero after screening in both the separate and joint models. Some direct-association inferences also changed. Because screening removed a substantial number of observations, including all four respondents reporting no AI use, these comparisons reflect changes in sample composition as well as precision. The full-sample results were retained as the primary findings, but the moderated mediation evidence should be interpreted as sensitive to case selection.

4. Discussion

This study examined the relationships between four dimensions of AI self-efficacy and academic procrastination, considering self-regulatory processes and AI use frequency. A central finding was the contrasting pattern for assistance self-efficacy: its direct association with procrastination was positive, whereas its indirect associations through self-monitoring and self-evaluation were negative. Anthropomorphic interaction showed a different pattern, with a positive indirect association through self-evaluation despite a nonsignificant direct association. The indirect associations through self-evaluation were smaller in magnitude at higher levels of AI use frequency. These findings highlight the importance of distinguishing among dimensions of AI self-efficacy and the self-regulatory processes associated with them.

4.1. Dimensions of AI Self-Efficacy and Academic Procrastination

The findings showed that the assistance of AI self-efficacy significantly and positively predicted academic procrastination. AI functions such as information retrieval, concept explanation, learning support, problem solving, and feedback can provide valuable support when students undertake academic tasks (Morales-García et al., 2024; Wang & Chuang, 2024). Nevertheless, perceived competence in obtaining assistance from AI does not necessarily mean that these technologies are always used deliberately, purposefully, or in ways that support self-regulation (Kasneci et al.,

2023). Galindo-Domínguez et al. (2026), for example, found that most students used AI for basic information retrieval and learning support, whereas a smaller group relied heavily on AI to complete academic tasks and make decisions. For some students, therefore, AI may shift from being a learning aid to becoming a primary source of cognitive support in the performance of academic tasks.

From this perspective, the key factor explaining academic procrastination may be not whether assistance is obtained from AI, but how that assistance is used. When students employ AI as a means of transferring academic responsibility and cognitive effort rather than as a tool that supports learning, their active involvement in planning, initiating, and sustaining tasks may decline. Canieso et al. (2025) showed that AI use could inadvertently delay students' initiation and completion of academic tasks. Excessive dependence on ChatGPT has likewise been reported to increase tendencies toward laziness and weaken creativity and independent thinking (Zhang et al., 2024). Positive associations between excessive or uncontrolled AI use and academic procrastination have also been reported in different samples (Lahmer, 2025; Mukhtar et al., 2025; Shu & Miao, 2021). One possible interpretation is that the positive association reflects reliance on AI as a substitute for students' own cognitive engagement. However, this form of reliance was not directly measured in the present study.

The findings further showed that comfort with AI and technological skills significantly and positively predicted academic procrastination. The rapid and readily accessible answers produced by AI tools may lead students to underestimate the effort required by academic tasks and delay initiation on the assumption that the work can still be completed later. When students perceive that AI enables academic tasks to be completed more quickly and with less effort, they may regard these tools as a last-minute "safety net" and postpone starting the task (Abbas et al., 2024). Thus, the positive associations of comfort with AI and technological skills with academic procrastination suggest that, as barriers to accessing and using AI diminish, the perceived cost of delaying tasks may also decrease.

In contrast, anthropomorphic interaction did not significantly predict academic procrastination directly. Wang and Chuang (2024) define anthropomorphic interaction as individuals' perceived ability to communicate with AI naturally, fluently, and reciprocally. The literature indicates that features that humanize chatbots enhance social presence, thereby strengthening socioemotional outcomes such as trust, perceived empathy, and satisfaction with the interaction (Araujo, 2018; Følstad & Brandtzæg, 2020; Qiu & Benbasat, 2009). Because academic procrastination is closely related to task initiation, time management, persistence of effort, and behavioral regulation (Zimmerman, 2000; Zimmerman & Schunk, 2011), the socioemotional benefits generated by anthropomorphic interaction may not, by themselves, have translated into a behavioral mechanism that prompted students to initiate or persist with academic tasks earlier. This result suggests that the effects of anthropomorphic interaction may be concentrated more in the social and affective quality of human–AI interaction than in academic behavior directly.

4.2. Dimensions of AI Self-Efficacy and Self-Regulation Skills

In Model 1, assistance from AI significantly and positively predicted self-monitoring, self-evaluation, and self-reinforcement. This result is consistent with research showing that AI support can enhance self-regulated learning across cognitive, metacognitive, and motivational dimensions. Achuthan's (2025) meta-analysis of 32 studies found a large positive effect of AI support on self-regulated learning ($g = 1.613$). By making the learning process visible through real-time feedback, learning dashboards, and adaptive guidance, AI systems can help students recognize their progress and errors and thereby support self-monitoring (Jin et al., 2023; Lan & Zhou, 2025; Qiao & Zhao, 2023). Likewise, personalized guidance, goal-setting support, and interaction logs can help students evaluate their performance and adjust subsequent learning strategies accordingly (Mitsea et al., 2023; Qiao & Zhao, 2023; Wu et al., 2024).

Jin et al. (2023) reported that students perceived AI applications as useful for cognitive, metacognitive, and behavioral regulation, although their perceived contribution to motivational

regulation was more limited. Personalized feedback and reflective interactions have nevertheless been found to help students identify their strengths and areas for improvement (Jin et al., 2023; Mitsea et al., 2023). From the perspective of Self-Determination Theory, satisfaction of the needs for autonomy, competence, and relatedness supports intrinsic motivation and learning satisfaction (Deci & Ryan, 2000). By providing timely feedback and personalized support, AI may strengthen perceptions of competence and autonomy and help students sustain their learning behaviors. In Zimmerman's (2000, 2002) model, self-reinforcement is also associated with positive self-reactions that follow individuals' evaluations of their performance. The positive association between assistance self-efficacy and self-reinforcement may reflect students' recognition of progress and perceived competence, although these explanations were not directly tested. Overall, assistance self-efficacy was positively associated with all three self-regulatory processes, although the findings do not establish the direction of these relationships.

In Model 2, anthropomorphic interaction significantly and negatively predicted only self-evaluation; it was not significantly associated with self-monitoring or self-reinforcement. It has been argued that, particularly during prolonged and close interactions, anthropomorphic AI features may lead users to attribute agency and decision-making competence to the system beyond its actual capabilities, thereby weakening autonomy and responsibility for independent decision making (Curș eu & Radu, 2026; Uysal et al., 2022; Watson, 2019). Within Self-Determination Theory, an overly directive role for AI may diminish students' perceived autonomy over learning and strengthen externally regulated tendencies (Deci & Ryan, 2000). One possible interpretation is that greater confidence in interacting with AI coincides with greater reliance on AI-generated guidance when evaluating performance. However, such reliance was not directly measured, and the findings cannot establish whether it precedes or follows lower self-evaluation. By contrast, self-monitoring involves continuous tracking of the learning process and performance, whereas self-reinforcement concerns motivational responses to performance (Zimmerman, 2000, 2002). Although anthropomorphic interaction may strengthen socioemotional features such as trust, social closeness, empathy, and natural communication (Howe et al., 2023), these features may not have been sufficient to activate self-monitoring or self-reinforcement directly.

In Model 3, comfort with AI was a significant positive predictor of self-reinforcement, whereas its associations with self-monitoring and self-evaluation were nonsignificant. This finding suggests that usability and self-regulated learning operate through different psychological mechanisms. In the Technology Acceptance Model, perceived ease of use refers to the belief that using a technology requires little effort and can influence perceived usefulness and the intention to use that technology (Davis, 1989). Accordingly, feeling comfortable using AI may not directly enable students to monitor or evaluate their learning more systematically; however, the low effort and successful experiences associated with use may support their perceptions of competence and satisfaction. It is therefore theoretically plausible that comfort with AI was related more strongly to self-reinforcement, which has a clearer motivational component, than to self-monitoring or self-evaluation.

In Model 4, AI-related technological skills did not significantly predict self-monitoring, self-evaluation, or self-reinforcement. This result suggests that technological competence and competence in regulating learning are conceptually distinct. The ability to use AI tools effectively reflects knowledge of the technology's functions and modes of use, whereas self-regulation requires students to plan, monitor, and evaluate their learning in accordance with their goals (Zimmerman, 2000, 2002). Technical competence alone may therefore be insufficient to activate these cognitive and motivational mechanisms. In other words, being able to use AI well and being able to use AI effectively to regulate one's own learning represent different domains of competence.

4.3. Self-Regulation Skills and Academic Procrastination

Self-monitoring and self-evaluation, two components of self-control and self-management, were significantly associated with lower academic procrastination. According to self-regulation theory,

individuals manage their behavior by monitoring it, evaluating it against personal standards, and readjusting it in light of the outcomes obtained (Bandura, 1991). From this perspective, self-monitoring provides information about current performance, whereas self-evaluation compares that information with goals and standards and thereby forms the basis for subsequent adjustments.

Self-monitoring enables individuals to track their behavior and its consequences continuously, identify discrepancies between their current state and their goals, and adjust the learning process when necessary (Tougas et al., 2015). Meta-analytic findings show that self-monitoring interventions significantly improve academic achievement (Hedges' g = 0.47) and the use of learning strategies (g = 0.38; Guo, 2022). Monitoring tools such as learning diaries and portfolios have similarly been reported to have a moderate effect on academic achievement (d = 0.42; Dignath et al., 2023).

Self-evaluation entails comparing information obtained through monitoring with personal goals, performance standards, and other criteria, and initiating corresponding behavioral adjustments (Tougas et al., 2015). A meta-analysis by Li et al. (2018) showed that self-evaluation had a substantial effect on academic achievement, while Panadero et al. (2017) found that self-assessment practices could enhance self-regulated learning and self-efficacy. These findings suggest that students' capacity to monitor their own learning and evaluate their performance against their goals may serve as a protective function by supporting the timely initiation and continuation of academic tasks.

Evidence concerning academic performance further supports this relationship. Consistent negative associations have been reported between academic achievement and academic procrastination (Ben Alaya et al., 2021; Kooren et al., 2024). Mastrokoukou et al. (2026) showed that self-regulation and self-efficacy were important mechanisms in the relationship between academic procrastination and academic achievement. Thus, students' monitoring of their learning, evaluation of their performance against their goals, and behavioral readjustment when necessary may help explain lower academic procrastination by supporting the timely initiation and continuation of academic tasks.

In contrast, self-reinforcement did not significantly predict academic procrastination. Whereas self-monitoring and self-evaluation are directly related to planning and monitoring academic tasks and readjusting behavior, self-reinforcement primarily serves to sustain motivational and affective responses to one's performance (Bandura, 1991; Neilans & Israel, 1981). Academic procrastination is closely related to regulatory processes such as initiating tasks, taking timely action, and sustaining behavior (Canieso et al., 2025). Positive self-reactions to success may therefore be insufficient, on their own, to alter these processes. This functional distinction may explain why self-reinforcement did not directly predict academic procrastination.

4.4. Mediating Roles of Self-Control-Self-Management Skills

The assistance model showed an inconsistent mediation pattern: its positive direct association with academic procrastination and negative total indirect association had opposite signs. The negative indirect associations through self-monitoring and self-evaluation opposed the positive direct association; consequently, assistance self-efficacy should not be characterized as uniformly associated with lower procrastination. Research on AI-supported learning has highlighted the relevance of real-time feedback, performance monitoring, and personalized guidance to students' monitoring and evaluation of their learning (Jin et al., 2023; Lan & Zhou, 2025; Qiao & Zhao, 2023; Wu et al., 2023). These functions provide a plausible context for the negative indirect associations. At the same time, confidence that AI assistance is readily available may coexist with a tendency to postpone tasks. This possible explanation for the positive direct association was not directly tested and requires further investigation.

Anthropomorphic interaction showed a positive indirect association with academic procrastination through self-evaluation, while the confidence intervals for its total and direct associations included zero. The component paths were both negative: anthropomorphic interaction

self-efficacy was negatively associated with self-evaluation, and self-evaluation was negatively associated with procrastination. Their product was therefore positive, distinguishing this pathway from the negative indirect associations in the assistance model. Self-evaluation involves reviewing performance against personal goals and standards and is central to self-regulated learning (Zimmerman, 2000, 2002). Research on anthropomorphic AI has emphasized trust and social presence in human–AI interaction (Araujo, 2018; Følstad & Brandtzæg, 2020; Qiu & Benbasat, 2009), while other work has raised concerns about attributing excessive agency and decision-making competence to AI (Uysal et al., 2022; Watson, 2019). These perspectives suggest that reliance on AI judgments may be relevant to understanding the observed association with self-evaluation. However, such reliance was not directly measured, and the cross-sectional findings do not establish that anthropomorphic interaction diminishes students' evaluative responsibility.

The absence of significant indirect associations through self-reinforcement, or for comfort with AI and technological skills, further distinguishes technical confidence from the regulation of learning. Although perceived ease of use is central to technology acceptance (Davis, 1989), comfort and technical competence do not necessarily involve monitoring progress or evaluating performance. Research on AI-supported self-regulated learning instead emphasizes feedback, personalized guidance, and explicit learning support (Achuthan, 2025; Jin et al., 2023; Lan & Zhou, 2025). The present findings are consistent with this distinction and highlight the importance of examining specific self-regulatory processes when interpreting the relationship between AI self-efficacy and academic procrastination.

The estimated indirect associations of assistance self-efficacy and anthropomorphic interaction with academic procrastination through self-evaluation were larger in absolute magnitude at AI use a few times a week than at daily AI use. This shared pattern indicates that the strength of the estimated indirect associations differs across levels of AI use frequency. Partly consistent with this pattern, intensive or problematic technology use has been associated with weakened self-regulation and increased academic procrastination (Jebasingh et al., 2025; Karakaya Özyer & Altınsoy, 2023). Evidence also indicates that AI use frequency may differentiate the relationship between students' performance control and self-regulatory processes (Roman et al., 2026). These findings identify differences in the magnitude of the indirect associations through self-evaluation across levels of AI use frequency. They do not establish that more frequent AI use changes self-regulation or procrastination.

5. Limitations

Several limitations should be considered when interpreting these findings. First, the cross-sectional design does not establish temporal ordering or causal relationships. A causal interpretation of the proposed mediation pathways would require AI self-efficacy to precede self-regulatory processes and these processes to precede academic procrastination. It would also require adequate control of confounding in the predictor–mediator, predictor–outcome, and mediator–outcome relationships, no mediator–outcome confounder caused by the predictor, and correct model specification. These assumptions cannot be established with the present design; the estimated indirect associations should therefore not be interpreted as evidence of causal mediation (Maxwell & Cole, 2007). Alternative temporal sequences are plausible. Students who habitually postpone academic tasks may subsequently seek AI assistance, with repeated use shaping their confidence in obtaining such support. Conversely, existing self-regulatory skills may precede and shape students' AI self-efficacy. Reciprocal relationships are also possible. Longitudinal and appropriately designed intervention studies are needed to distinguish these alternatives from the proposed ordering. Second, all variables were assessed using self-report measures collected from the same participants at a single time point, creating a risk of common method bias that may have influenced the observed associations. Third, participants were recruited through convenience sampling from a single faculty of education, limiting the generalizability of the findings to students in other disciplines and institutional contexts. Participants were drawn from multiple programs and year levels within a single faculty. Although HC3 heteroskedasticity-consistent standard errors were

used, the analyses did not account for potential clustering within programs or classes. Shared instructional contexts may therefore have affected the precision of the estimates. Women constituted 74.1% of the sample, which also limits the extent to which the findings represent a more gender-balanced student population. Finally, 98.6% of participants reported previous AI use. The results therefore primarily reflect students with prior AI experience and provide limited insight into those unfamiliar with these tools. Together, these limitations constrain both the interpretation of the proposed pathways and their applicability beyond the sampled population.

6. Suggestions

6.1. Implications for Practice

The findings suggest possible directions for designing AI-supported learning activities, but they do not demonstrate that particular instructional practices reduce procrastination. Curriculum developers and university faculty could investigate activities that combine AI assistance with staged deadlines, progress monitoring, and explicit evaluation of AI-generated outputs. For example, students could explain why they accepted or rejected AI suggestions and document their own contribution to an assignment. These approaches are consistent with calls to integrate AI literacy into teacher education (Açıkyıldız & Şahin, 2025), but their associations with task initiation and completion require longitudinal investigation and their effectiveness should be tested through interventions.

Institutions could also provide pilot guidance on appropriate AI use, output verification, and transparent disclosure, alongside professional development for faculty. Such initiatives should address the purpose and quality of AI use rather than assume that frequency alone determines its educational value. Given the cross-sectional design and the sensitivity of the moderated mediation findings to case selection, these proposals should be treated as practices to evaluate rather than established consequences of the present results.

6.2. Suggestions for Researchers

Future research should examine AI use not only in terms of frequency but also with regard to purpose, task type, duration, and the stages of academic work at which students seek AI support. The distinct relationships of the dimensions of AI self-efficacy with academic procrastination in this study suggest that treating AI self-efficacy as unidimensional may obscure specific mechanisms. Future studies should therefore examine assistance, technological skills, comfort with AI, and anthropomorphic interaction separately and investigate how these dimensions interact with different self-regulatory processes. Mechanisms such as cognitive offloading, AI dependence, metacognitive awareness, and problematic AI use should also be investigated to examine why the indirect associations through self-evaluation differ across levels of AI use frequency. Longitudinal and experimental studies could help overcome the causal limitations of cross-sectional research by clarifying the direction of the relationships among AI use, self-regulation, and academic procrastination and how they change over time.

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Data availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to applicable ethical and privacy restrictions.

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