

Article

Understanding Student Dependency on AI: The Role of AI Literacy, Academic Self-Efficacy, and Resource Management Strategies

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Abstract

The integration of artificial intelligence (AI) tools in higher education raises important questions about how students engage with these technologies and what shapes that engagement. This study examined how AI literacy, academic self-efficacy, and self-regulated resource management strategies are associated with students' reported AI dependency. Participants were 478 students from Israeli higher education institutions who completed a cross-sectional online survey assessing AI dependency, AI literacy (four subscales), academic self-efficacy, and resource management strategies (time and study management, effort regulation, and help seeking). Multiple regression and K-means cluster analysis were used. The skill-based dimensions of AI literacy were positively associated with AI dependency, whereas AI self-efficacy and academic self-efficacy were both negatively associated, suggesting a unified compensatory self-efficacy mechanism. Effort regulation also predicted lower dependency, while general academic help seeking predicted higher dependency. The model explained 27.3% of the variance in AI dependency. Cluster analysis identified four learner profiles differing in literacy-dependency combinations and in self-regulatory resources. The findings suggest that fostering AI literacy alone is insufficient. Developing students' self-efficacy beliefs and self-regulated learning practices appears equally important for promoting balanced and intentional AI engagement in higher education.

Keywords: AI dependency; AI literacy; academic self-efficacy; generative artificial intelligence; self-regulated learning; higher education

1. Introduction

AI-based systems, ranging from intelligent tutoring platforms to generative language models such as ChatGPT, are increasingly embedded in university learning environments (Ng et al., 2024). While AI can enhance accessibility, efficiency, and personalization in education, it may also encourage overreliance and reduce opportunities for the development of essential cognitive and metacognitive skills (Selwyn, 2019; Zawacki-Richter et al., 2019). Understanding how and why students depend on AI has therefore become a central concern for educators and researchers (Zhang et al., 2024). AI dependency is unlikely to stem from a single source. Rather, it emerges from the interplay between students' competencies, beliefs, and learning strategies. The present study advances an integrative theoretical model developed in detail in Section 1.6 in which AI dependency is conceptualized as the joint product of three theoretically distinct psychological mechanisms: AI literacy as an enabling cognitive capacity (Risko & Gilbert, 2016), academic self-efficacy as a compensatory motivational factor (Kardefelt-Winther, 2014), and self-regulated resource



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management strategies as the behavioral routines through which motivational tendencies are translated into action (Pintrich et al., 1993; Zimmerman, 2000).

Although prior research has investigated each of these constructs separately, linking AI literacy to responsible use (Long & Magerko, 2020), academic self-efficacy to problematic AI behavior (Zhang et al., 2024), and self-regulation to learning outcomes in technology-rich environments (Ng et al., 2024), no integrative framework has yet specified how they jointly shape AI dependency. The proposed model addresses this gap by generating directional hypotheses, formalized in Section 1.7. AI literacy is predicted to be positively associated with AI dependency (enabling-capacity mechanism); academic self-efficacy is predicted to be negatively associated with AI dependency (compensatory mechanism); and resource management strategies are predicted to operate heterogeneously, with help seeking channeling dependency, effort regulation buffering against it, and time management showing a weaker association. Examining these mechanisms together is essential for clarifying why some students integrate AI as a complementary learning resource while others come to rely on it in ways that may compromise their academic development. Accordingly, the present study aims to examine how AI literacy, academic self-efficacy, and self-regulated resource management strategies jointly predict students' dependency on AI among students.

1.1. Artificial Intelligence in Higher Education

Artificial intelligence (AI) has rapidly become an influential force in higher education, transforming how students access information, engage with learning materials, and complete academic tasks. AI refers to computational systems capable of performing functions typically associated with human intelligence, including learning, reasoning, language processing, and problem solving (Russell & Norvig, 2021). The recent development of generative AI and large language models (LLMs), such as ChatGPT, has further expanded the role of AI in academic contexts by enabling students to generate written content, receive explanations, and obtain immediate feedback on academic tasks (Dwivedi et al., 2023; Kasneci et al., 2023).

In educational settings, AI technologies offer a wide range of opportunities. Intelligent tutoring systems, automated feedback tools, and generative AI applications can provide personalized learning experiences and support students in complex learning tasks (Holmes et al., 2019; Luckin et al., 2016). At the same time, the growing integration of AI in education raises important concerns regarding its potential impact on learning processes. Scholars have argued that excessive reliance on AI tools may reduce opportunities for students to develop essential academic skills such as critical thinking, problem solving, and independent reasoning (Selwyn, 2019; Zawacki-Richter et al., 2019). Generative AI systems may also produce inaccurate or biased information, raising questions about academic integrity and the reliability of AI-generated knowledge in educational contexts (Kasneci et al., 2023).

Given the increasing presence of AI tools in academic environments, understanding how students engage with these technologies has become an important research priority. Understanding students' dependency on AI requires specific attention to generative AI environments, where the boundaries between assistance and substitution of cognitive effort become increasingly blurred. Scholars emphasize that students' interaction with AI cannot be explained solely by access to technology but must also be understood through psychological and learning-related factors that shape their use of these systems (Dwivedi et al., 2023). In particular, students' technological competencies, motivational beliefs, and self-regulated learning strategies may influence how they incorporate AI into their academic work.

1.2. Dependency on AI in Learning

The growing use of artificial intelligence tools in academic contexts has led to increasing attention to the phenomenon of AI dependency. Academic dependency on AI refers to a pattern of excessive reliance on artificial intelligence technologies for performing cognitive or academic tasks that traditionally require independent intellectual effort (Morales-García et al., 2024).

Theoretically, AI dependency can be positioned within broader frameworks that examine how humans interact with cognitive tools and automated systems. The construct of cognitive offloading describes the use of external resources to reduce internal cognitive demand. Although such offloading can be adaptive when it frees mental resources for higher-order reasoning, it may become maladaptive when it consistently substitutes for, rather than supports, learners' own thinking (Risko & Gilbert, 2016). Research on human-automation interaction further distinguishes between calibrated and miscalibrated reliance: appropriate reliance involves accepting accurate machine output and rejecting inaccurate output, whereas overreliance reflects an uncritical acceptance of automated suggestions (Lee & See, 2004). Closely related is the concept of automation bias, the tendency to favor automated outputs over independent judgment, particularly under conditions of high cognitive load or time pressure (Parasuraman & Manzey, 2010). Within this conceptual landscape, AI dependency can be understood as a maladaptive form of reliance, in which the use of AI tools moves beyond strategic cognitive offloading toward a sustained pattern of overreliance and reduced engagement in independent academic effort.

It is therefore important to distinguish between frequent use of AI tools and dependency on AI. While frequent use may reflect adaptive and efficient learning strategies, a form of strategic offloading that supports learning, dependency implies a reduced tendency to engage in independent cognitive effort and an increased reliance on automated solutions even when such reliance is not necessary. In this sense, AI dependency reflects not only behavioral patterns of use but also underlying motivational and regulatory processes.

A scale designed to measure dependency on artificial intelligence among university students has been developed and validated by Morales-García et al. (2024). Their work conceptualizes AI dependency as a behavioral and psychological tendency to rely on AI systems for tasks such as generating academic content, solving problems, or making decisions, an understanding consistent with broader accounts of overreliance and maladaptive cognitive offloading in human-technology interaction. The validation of the instrument demonstrated that dependency on AI may involve patterns of reduced cognitive effort and increased reliance on automated solutions in academic tasks.

The literature identifies several potential consequences of AI dependency. One concern is the erosion of essential academic skills, sometimes referred to as skill atrophy, whereby students reduce practice in writing, analytical reasoning, and argument development due to reliance on automated tools (Zawacki-Richter et al., 2019). Another concern relates to academic integrity, as AI systems may facilitate forms of unauthorized assistance that undermine the development of independent learning (Arce et al., 2025). Recent studies examining students' interaction with generative AI technologies indicate that AI tools are increasingly used for writing assistance, idea generation, and problem solving (Kasneci et al., 2023). While such tools may support learning, excessive reliance on them may reduce opportunities for deeper cognitive engagement with academic material. Understanding the factors that shape students' dependency on AI represents, therefore, an important direction for research in higher education. This distinction implies that dependency cannot be inferred from usage frequency alone. Rather, it must be understood in light of the learner's competencies, motivational resources, and regulatory practices.

1.3. AI Literacy in Higher Education

[Carolus et al. \(2023\)](#) define AI literacy as the set of abilities, knowledge, and skills that allow a person to understand, identify, use, and evaluate artificial intelligence systems in different contexts. This is not just deep technical knowledge or the ability to develop AI systems (as in programming, for example) but mainly includes the ability to understand what artificial intelligence is, how it works, what its possibilities and limitations are, and how it can be used intelligently in everyday and professional situations. In addition, it also includes aspects of understanding such as what are the social implications of the widespread use of artificial intelligence. As in other definitions (e.g., [Southworth et al., 2023](#)), this definition comprises four key components: knowing and understanding AI, using and applying AI, identifying (detecting) AI, and ethical aspects of AI. The ability to create AI is not seen as a necessary part of AI literacy but as a separate skill, in this definition.

There are numerous benefits of AI literacy. [Laupichler et al. \(2022\)](#) claim that AI literacy is vital for everyone in society, as it enables individuals to effectively engage with opportunities and challenges posed by AI technology in personal and professional lives. They further argue that AI literacy helps students develop their critical thinking skills and the ability to write informed arguments using AI in various technologies. According to [Southworth et al. \(2023\)](#), AI literacy will help students develop the necessary skills to succeed in the modern workforce, with the goal of providing them with the knowledge and competencies essential for thriving in the 21st-century job market. [Pierres et al. \(2024\)](#) write that AI literacy is crucial in higher education, as it helps manage students' expectations and raises awareness of potential risks associated with AI technologies, including biases and privacy concerns.

1.4. Academic Self-Efficacy

Academic self-efficacy refers to individuals' beliefs about their ability to successfully perform academic tasks ([Bandura, 1986](#)). According to social cognitive theory, these beliefs play a central role in shaping students' motivation, persistence, and academic performance ([Pajares, 2002](#)). Students with higher academic self-efficacy typically demonstrate greater confidence in their ability to plan, organize, and complete academic work. They are more likely to invest effort in challenging tasks, persist in the face of difficulties, and adopt effective learning strategies ([Honicke & Broadbent, 2016](#)). Conversely, students with lower levels of academic self-efficacy may experience higher levels of academic anxiety and uncertainty regarding their ability to perform academic tasks successfully.

Previous studies also suggest that self-efficacy is closely related to students' use of self-regulated learning strategies. Learners with stronger self-efficacy beliefs tend to engage more actively in regulating their learning processes and managing academic resources ([Pintrich, 2004](#)). In the digital environment, this tendency is increasingly evident in the growing reliance on AI tools such as ChatGPT. These platforms provide fast and convenient answers to academic queries, potentially improving short-term performance ([Alshater, 2022](#)). However, overreliance on such tools may undermine the development of independent learning skills and lead to AI dependency, a pattern characterized by both habitual and psychological reliance on artificial intelligence in academic and everyday settings. The IPACE model (Interaction of Person–Affect–Cognition–Execution) also supports the link between low self-efficacy and maladaptive technology use ([Zeng et al., 2021](#)). A previous study found an inverse relationship between academic self-efficacy and problematic digital behaviors, including internet and technology addiction ([Beranuy et al., 2009](#); [Odaci, 2011](#)). These findings suggest that academic self-efficacy may play an important role in shaping how students interact with AI technologies in educational contexts.

1.5. Self-Regulated Resource Management Strategies in Higher Education

Self-regulated learning refers to the processes through which learners actively plan, monitor, and regulate their cognitive, motivational, and behavioral activities to achieve academic goals (Zimmerman, 2000). Within this framework, resource management strategies represent an important component of self-regulation. One of the most widely used instruments for measuring self-regulated learning in higher education is the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich et al. (1993). Within the MSLQ framework, resource management strategies include three primary components: time and study environment management, help seeking, and effort regulation. Research consistently demonstrates that these strategies are strongly associated with academic success and effective learning behaviors (Credé & Phillips, 2011).

1.5.1. Time Management

Time and study environment management refers to students' ability to plan and organize their academic schedules and to structure learning environments in ways that support effective study (Pintrich et al., 1993). Effective time management enables students to allocate sufficient time for academic tasks and maintain consistent study habits. Empirical research indicates that time management is positively associated with student engagement, academic achievement, and reduced procrastination (Wolters & Brady, 2021; Wolters et al., 2017). Time management also supports forethought (e.g., goal setting), performance (e.g., task monitoring), and self-reflection (e.g., evaluating time use), thereby bridging the gap between intention and execution. Individual differences in students' preferences for organization, pacing, and goal setting significantly influence their likelihood to procrastinate and their capacity for sustained learning efforts (Wolters & Brady, 2021; Wolters et al., 2017). Recent studies have also highlighted time-estimation bias, the tendency to inaccurately assess how long tasks will take, as a key barrier to effective time management. These biases can distort planning, resulting in increased stress and incomplete academic tasks (Brady et al., 2022).

1.5.2. Help Seeking

Help seeking represents a self-regulatory strategy through which learners seek assistance when encountering difficulties during learning (Newman, 1994). Within the framework of self-regulated learning, help seeking allows students to obtain support while maintaining engagement with academic tasks. Research distinguishes between instrumental help seeking, which aims to enhance understanding and promote autonomous problem solving, and executive help seeking, which focuses on completing tasks without deeper learning (Karabenick & Newman, 2006). Adaptive help-seeking behaviors have been linked to greater academic persistence and improved learning outcomes (Ryan et al., 2005).

However, emotional and social barriers—such as cultural norms that stigmatize admitting difficulty—often discourage students from seeking support (Ryan et al., 2005). A recent study by Chen and Son (2024) provides new insights into the psychological impediments to help seeking, finding that individuals with high impostor feelings, those who believe their success is accidental or unearned, are significantly less likely to ask for help, particularly in challenging subjects such as mathematics. These findings underscore the importance of creating educational contexts that not only teach help seeking as a skill but also actively address affective barriers—such as impostorism and stigma—to support adaptive academic self-regulation.

1.5.3. Effort Regulation

The concept of effort regulation refers to a student's ability to persist in academic tasks despite distractions, difficulty, or fatigue (Pintrich & De Groot, 1990). It reflects a

motivational commitment to task completion and is a critical factor in determining the quality and quantity of cognitive engagement. Students who demonstrate strong effort regulation are more likely to succeed in challenging academic environments because they maintain consistent work habits and persist through setbacks (Honicke & Broadbent, 2016; Richardson et al., 2012; Wolters, 1998). In contrast, students with low effort regulation often disengage early, particularly in self-paced or digital learning contexts where external structure is minimal. Effort regulation is often influenced by students' goal orientation, with mastery-oriented learners tending to exhibit higher persistence than performance-avoidant learners (Elliot & McGregor, 2001).

1.6. The Present Study

Although the integration of AI technologies into teaching and learning has rapidly expanded in recent years (Lin et al., 2024; Sozon et al., 2025), empirical research remains limited in explaining the personal and cognitive factors that predict students' levels of dependency on these technologies. Prior research has typically examined AI literacy, academic self-efficacy, and self-regulated learning strategies as separate predictors of AI use but has not articulated a unified theoretical account of how these factors jointly shape AI dependency. Drawing on social cognitive theory (Bandura, 1986), the cognitive offloading framework (Risko & Gilbert, 2016), and Compensatory Internet Use Theory (Kardefelt-Winther, 2014), we propose an integrative model in which AI dependency emerges from the interplay of three theoretically distinct mechanisms: an enabling capacity, a compensatory motivation, and a self-regulatory function.

The enabling-capacity mechanism (AI literacy as a multidimensional construct). AI literacy is conventionally framed as a protective competency that promotes critical and autonomous engagement with AI tools (Laupichler et al., 2022; Southworth et al., 2023). However, the construct as captured by recent instruments such as the MAILS (Carolus et al., 2023) is in fact multidimensional, encompassing both skill-based dimensions (knowing, understanding, using, applying, and detecting AI) and belief-based dimensions (notably, self-efficacy in AI use). These dimensions are theoretically distinct and may operate through opposing mechanisms with respect to AI dependency. From a cognitive offloading perspective (Risko & Gilbert, 2016), the skill-based dimensions function as an enabling capacity: greater technical proficiency lowers the perceived effort required to delegate cognitive tasks to AI and expands the range of academic activities that students can plausibly outsource. Consistent with broader models of technology adoption, in which expertise accelerates rather than restrains use (Venkatesh et al., 2003), recent studies show that AI literacy positively predicts both behavioral intentions and actual use of generative AI tools (Wang et al., 2025). The belief-based dimension—AI self-efficacy—is treated separately in the present model as part of the compensatory-motivation mechanism described below.

The compensatory-motivation mechanism (self-efficacy beliefs, academic and AI-specific). Compensatory Internet Use Theory (Kardefelt-Winther, 2014) and the I-PACE model (Brand et al., 2016; Zeng et al., 2021) propose that problematic technology use often emerges from a motivational need to compensate for perceived deficiencies in coping resources. Applied to academic AI use, students with low academic self-efficacy may turn to AI tools to alleviate uncertainty about their ability to perform academic tasks, using AI as an external substitute for confidence in their own abilities. Zhang et al. (2024), drawing on the I-PACE model, found that academic self-efficacy was indirectly related to AI dependency through academic stress and performance expectations, and Morales-García et al. (2024) similarly observed an inverse correlation between academic self-efficacy and AI dependency. These findings parallel earlier research on problematic Internet and smartphone use, which has consistently linked low self-efficacy to maladaptive technology

engagement (Beranuy et al., 2009; Odaci, 2011). Drawing on Bandura's (1997) view of self-efficacy as inherently domain-specific, we extend this account to a second, AI-specific compensatory pathway: students who feel competent and confident specifically in their interaction with AI tools (AI self-efficacy) are expected to experience less motivational pressure to over-rely on AI, just as students with strong academic self-efficacy do in the broader academic domain. Self-efficacy beliefs are therefore positioned in our model as a unified compensatory mechanism that operates across both general academic and AI-specific domains, with both forms of self-efficacy expected to attenuate AI dependency.

The self-regulatory mechanism (resource management strategies). Within Zimmerman's (2000) self-regulated learning framework, resource management strategies are the behavioral mechanisms through which motivational beliefs are translated into sustained academic action. Effort regulation, the capacity to persist despite difficulty or fatigue, is theorized to protect students from overreliance on AI by maintaining independent engagement with learning tasks even when AI shortcuts are available. Empirical research supports this protective role: effort regulation has been consistently linked to lower academic procrastination, higher persistence, and reduced engagement with distracting digital media (Elizondo et al., 2024; Wolters & Brady, 2021). Help seeking, by contrast, is theoretically ambivalent. Karabenick and Newman (2006) distinguished between instrumental help seeking, oriented toward deeper understanding and autonomous problem solving, and executive help seeking, oriented toward task completion through ready-made solutions. When applied to AI tools, this distinction is particularly consequential: AI's capacity to deliver immediate and complete answers may channel help-seeking behavior toward the executive end of the spectrum, transforming it from an adaptive strategy into a substitutive one. This interpretation is consistent with recent evidence that students increasingly turn to generative AI for immediate, task-focused assistance in their academic work, valuing its speed and instant feedback over slower, more effortful forms of learning support (Zhao et al., 2025). Help seeking, when channeled through AI, may therefore predict greater dependency rather than function as a regulatory strength. Finally, time and study environment management is theorized to operate primarily at a logistical-organizational level rather than at the motivational-emotional level that characterizes AI dependency, and is therefore expected to show a weaker association with the construct.

Taken together, the model proposes that AI dependency reflects neither a single behavioral tendency nor a simple consequence of technology access, but rather the joint operation of three mechanisms: a cognitive capacity that enables AI use, a motivational state that generates compensatory demand for AI assistance, and behavioral regulatory practices that either sustain or undermine independent engagement. This framework also informs the second goal of the present study, namely the identification of distinct learner profiles based on AI literacy and dependency. Because AI literacy and AI dependency are theorized to reflect partly independent mechanisms, students may exhibit qualitatively different combinations (e.g., high literacy with high dependency vs. high literacy with low dependency) that cannot be captured by linear models alone. Cluster analysis is therefore used to complement the regression analysis with a person-centered view of how the proposed mechanisms manifest in identifiable learner profiles.

1.7. Research Questions

The present study addresses three research questions, one confirmatory (RQ1) and two exploratory (RQ2 and RQ3):

RQ1. How do AI literacy, academic self-efficacy, and self-regulated resource management strategies relate to students' reported dependency on AI tools?

RQ2. What student profiles emerge when considering levels of AI literacy and AI dependency?

RQ3. In what ways do these profiles differ in their utilization of self-regulated resource management learning strategies?

RQ1 is tested through three directional hypotheses, each derived from one of the three theoretical mechanisms specified in the integrative model (Section 1.6).

H1 (enabling-capacity mechanism, skill-based AI literacy). *Consistent with the cognitive-offloading account developed in Section 1.6, the skill-based dimensions of AI literacy lower the effort of delegating academic tasks to AI and may therefore intensify rather than restrain its use. Accordingly:*

H1a. *Higher skill-based AI literacy (using/understanding and detecting AI) will be associated with higher reported AI dependency.*

H2 (compensatory self-efficacy mechanism, general academic and AI-specific). *Building on Bandura's (1997) domain-specific conception of self-efficacy and on Compensatory Internet Use Theory (Kardefelt-Winther, 2014), students who feel competent and confident, whether in general academic functioning or specifically in AI use, are expected to experience less motivational pressure to over-rely on AI (Morales-García et al., 2024; Zhang et al., 2024). Accordingly:*

H2a. *Higher academic self-efficacy will be associated with lower reported AI dependency.*

H2b. *Higher AI self-efficacy will be associated with lower reported AI dependency, paralleling the protective role of academic self-efficacy.*

H3 (self-regulatory mechanism). *Because the three resource-management strategies are theorized to operate through different pathways, H3 is disaggregated into three sub-hypotheses:*

H3a. *Stronger effort regulation will be associated with lower reported AI dependency, reflecting the buffering role of sustained engagement against shortcut-driven AI use (Elizondo et al., 2024).*

H3b. *Stronger general academic help seeking will be associated with higher reported AI dependency, reflecting the possibility that help seeking, when extended to AI tools, may channel reliance through executive rather than instrumental routes (Karabenick & Newman, 2006; Zhao et al., 2025).*

H3c. *Time and study environment management will show a weaker (non-significant) association with AI dependency, because it operates primarily at a logistical-organizational level rather than at the motivational-emotional level that characterizes AI dependency.*

RQ2 and RQ3 are addressed exploratorily, through cluster analysis on AI literacy and AI dependency, followed by ANOVAs comparing the resulting profiles on self-efficacy and resource management strategies (see Section 3).

2. Materials and Methods

2.1. Participants

Participants were 478 students enrolled in higher education institutions in Israel. Inclusion criteria were: (a) being 18 years of age or older; (b) being actively enrolled as a student in a recognized Israeli higher education institution at the time of data collection. Of the 478 participants, 228 (47.7%) were enrolled in academic colleges and 250 (52.3%) in universities. One hundred and sixteen participants were male (24%) and 362 female (76%), with a mean age of 25.8 years ($SD = 4.3$). With respect to degree level, 379 (79%) were pursuing a BA degree, 74 (15.5%) an MA or PhD degree, and 25 (5%) were enrolled in post-secondary academic tracks (practical engineering) within recognized higher education institutions. The required sample

size for the planned multiple regression and cluster analyses was determined according to the formal rule of $N \geq 50 + 8k$, where k is the number of predictors (Tabachnick & Fidell, 2013). With four predictors, the recommended minimum is 82 participants. The achieved sample ($N = 478$) substantially exceeds this minimum and is well above thresholds recommended for stable K-means cluster solutions (Hair et al., 2019), providing adequate statistical power for the multiple regression and cluster analyses reported in Section 3.

2.2. Procedure

Data were gathered between August and September 2025 through an online questionnaire administered via Panel4All, a commercial Israeli online survey platform that maintains a registered pool of approximately 100,000 active adult panelists. Recruitment was conducted by Panel4All by sending email invitations to panel members who matched the study's eligibility profile (adults aged 18 or older who self-identified as students in Israeli higher education institutions). Participants received panel-internal credit points for completing the survey, which could subsequently be redeemed for shopping vouchers. No additional incentives were offered by the research team. Duplicate participation was prevented through the platform's unique-respondent tracking system, which links each completed response to a verified panelist account.

2.3. Measures

- (1) AI dependency was assessed with the 5-item scale developed and validated by Morales-García et al. (2024). The scale measures students' overreliance on AI and the extent to which AI tools have become integrated into their academic routines (e.g., "I postpone my learning tasks when there is a technical problem with AI"). Items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), and a total score was computed as the mean of all items, with higher scores reflecting greater AI dependency. Internal consistency in the present sample was $\alpha = 0.85$.
- (2) AI literacy was assessed with the 20-item Meta AI Literacy Scale (MAILS; Carolus et al., 2023), which captures four conceptually distinct components of AI literacy: knowledge and understanding of AI, the ability to use and apply AI, the ability to identify (detect) AI, and ethical aspects of AI (e.g., "I recognize AI limitations"). All items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Consistent with the unidimensional treatment adopted in prior research using the MAILS (Carolus et al., 2023), a total AI literacy score was calculated as the mean of all items. Internal consistency in the present sample was $\alpha = 0.91$ for the total score, and $\alpha = 0.95$ (using and applying AI), $\alpha = 0.89$ (knowing and understanding AI), $\alpha = 0.78$ (detecting AI), and $\alpha = 0.64$ (ethics and emotional regulation in AI use) for the four subscales, respectively. The ethics-related subscale showed lower internal consistency than the other three components.
- (3) Academic self-efficacy was measured with the 8-item Self-Efficacy for Learning and Performance subscale of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993), which assesses students' expectancy for success and confidence in their ability to master academic material (e.g., "I am certain that in the end I will master the required academic skills"). Self-regulated resource management strategies were measured with three additional MSLQ subscales: time and study environment management (8 items, e.g., "I find it hard to stick to the schedule I planned"), effort regulation (4 items), and help seeking (4 items, e.g., "When I find something to be difficult, I try to solve it by myself without asking for help"). It is important to note that the MSLQ help-seeking subscale measures students' general academic help seeking from human sources (peers, instructors, teaching assistants) and does not refer

specifically to help seeking from AI tools. All items were rated on a 7-point Likert scale (1 = not at all true of me to 7 = very true of me), and subscale scores were computed as the mean of items. Internal consistency in the present sample was $\alpha = 0.94$ for academic self-efficacy, $\alpha = 0.77$ for time and study environment management, $\alpha = 0.72$ for effort regulation, and $\alpha = 0.67$ for help seeking.

- (4) A demographic questionnaire gathered participants' characteristics such as age, gender, and type of institution. The questionnaires were administered in Hebrew following a forward-backward translation and cross-cultural adaptation procedure to ensure linguistic, conceptual, and cultural equivalence between the original and translated versions (Brislin, 1970; Beaton et al., 2000).

2.4. Analysis

All analyses were performed using IBM SPSS Statistics v.30. Prior to inferential testing, we computed descriptive statistics (means, standard deviations) and zero-order Pearson correlations among all study variables (see Table 1). Of the 492 participants, 14 (2.8%) had missing data on AI dependency (the dependent variable) and were excluded via listwise deletion, yielding an analytic sample of $N = 478$ used in both the regression and the cluster/ANOVA analyses. No additional cases had missing data on the AI literacy or MSLQ subscales used as predictors due to the platform's forced-response design. Participants who failed attention checks were excluded prior to analysis. To address the research questions, we conducted (a) a multiple linear regression analysis predicting AI dependency from AI literacy, academic self-efficacy, time and study environment management, effort regulation, and help seeking; (b) a K-means cluster analysis on standardized AI literacy and AI dependency scores and (c) one-way ANOVAs comparing the resulting clusters on academic self-efficacy and resource management strategies, followed by Tukey HSD post hoc tests. For the regression model, multicollinearity was assessed using variance inflation factors (VIFs) and tolerance values. All predictors yielded VIF values between 1.08 and 1.87 (tolerance values between 0.53 and 0.92), well within accepted thresholds ($VIF < 5$; Hair et al., 2019), indicating that multicollinearity did not threaten the estimation of regression coefficients. For the cluster analysis, AI literacy and AI dependency scores were z-standardized prior to K-means clustering. The optimal number of clusters was determined by inspecting silhouette coefficients across 2- through 6-cluster solutions and examining the conceptual coherence of each solution. The 4-cluster solution yielded a silhouette coefficient of 0.64 (acceptable; Kaufman & Rousseeuw, 1990) and was selected over competing solutions because it provided the clearest theoretical differentiation among groups while preserving adequate group sizes (all $n \geq 89$). Effect sizes for the ANOVAs were estimated using partial eta-squared.

Table 1. Means, standard deviations, and bivariate correlations among study variables ($N = 478$).

Variable	1	2	3	4	5	6	7	8	9
1. AI Dependency	-								
2. AI Using/Understanding	0.38 **	-							
3. AI Detection	0.19 **	0.51 **	-						
4. AI Self-Efficacy	0.018	0.48 **	0.59 **	-					
5. AI Emotional Regulation	0.07	0.39 **	0.36 **	0.37 **	-				
6. Academic Self-Efficacy	−0.24 **	0.12 **	0.19 **	0.38 **	0.19 **	-			
7. Time/Study Management	−0.24 **	−0.05	−0.00	0.19 **	0.00	0.46 **	-		
8. Effort Regulation	−0.29 **	−0.03	0.02	0.21 **	0.08 *	0.55 **	0.61 **	-	
9. Help Seeking	0.06	0.11 *	0.01	0.14 **	0.03	0.27 **	0.25 **	0.18 **	-

Note. * $p < 0.05$; ** $p < 0.01$. Means and standard deviations are reported in Tables 2–4 below and in Section 2.3 (measures).

Table 2. Prediction of AI dependency by AI literacy subscales, academic self-efficacy, and resource management strategies.

Predictor Variable	<i>B</i>	<i>SE</i>	β	<i>t</i>	<i>p</i>
AI Literacy subscales					
Using and Understanding AI	0.41	0.05	0.404	8.19	<0.001
Identifying/Detecting AI	0.105	0.05	0.108	2.05	0.041
AI Self-Efficacy	−0.20	0.08	−0.132	−2.41	0.016
Emotional Regulation in AI Use	−0.03	0.04	−0.035	−0.78	0.43
Academic Functioning					
Academic Self-Efficacy	−0.18	0.05	−0.20	−3.81	<0.001
Time/Study Environment	−0.04	0.05	−0.05	−0.89	0.374
Management					
Effort Regulation	−0.11	0.04	−0.13	−2.48	0.013
Help Seeking	0.09	0.03	0.12	2.97	0.003

Note. $F(8, 469) = 22.03$, $R^2 = 0.273$, adjusted $R^2 = 0.261$, $p < 0.001$. $N = 478$.

Table 3. Cluster analysis by AI literacy and AI dependency: cluster sizes and means.

Profile	AI Dependency M (SD)	AI Literacy M (SD)	<i>n</i>	%
High Literacy, Low Dependency (HL)	1.44 (0.36)	3.85 (0.44)	156	32.6%
Moderate Literacy, Moderate Dependency (MM)	2.55 (0.36)	3.25 (0.41)	127	26.6%
Low Literacy, Low Dependency (LL)	1.27 (0.29)	2.51 (0.46)	110	23.0%
High Literacy, High Dependency (HH)	3.59 (0.46)	3.87 (0.46)	85	17.8%
Total	2.08 (0.94)	3.39 (0.70)	478	100%

Table 4. Comparison of clusters on resource management strategies and academic self-efficacy (one-way ANOVA with Tukey HSD).

Variable	HL (<i>n</i> = 156)	MM (<i>n</i> = 127)	LL (<i>n</i> = 110)	HH (<i>n</i> = 85)	<i>F</i> (3, 474)	η^2
Academic Self-Efficacy					22.60 ***	0.13
<i>M</i>	6.14 ^c	5.18 ^a	5.65 ^b	5.57 ^b		
<i>SD</i>	0.85	1.01	1.15	0.96		
Time/Study Environment Management					11.21 ***	0.07
<i>M</i>	5.19 ^b	4.60 ^a	4.90 ^{ab}	4.48 ^a		
<i>SD</i>	1.12	0.86	1.12	1.10		
Effort Regulation					19.00 ***	0.11
<i>M</i>	5.82 ^b	4.93 ^a	5.50 ^b	4.95 ^a		
<i>SD</i>	1.08	1.10	1.13	1.25		
Help Seeking					2.01 ns	0.01
<i>M</i>	4.09	3.83	3.84	4.18		
<i>SD</i>	1.47	1.07	1.32	1.16		

Note: Different superscript letters indicate significant differences between groups. *** $p < 0.001$. ns = not significant.

2.5. Ethical Considerations

All procedures were conducted in accordance with the ethical principles of the Declaration of Helsinki and the journal's policy on research ethics. The study was reviewed and approved by the Institutional Ethics Committee of the Research Authority at the researchers' academic institution (Approval No. 1215), with approval granted on 19 August 2024. All respondents participated voluntarily and were presented with a digital informed consent form before beginning the questionnaire. Participants could continue only after actively

providing their consent. The consent form explicitly clarified that (a) participation was voluntary, (b) respondents could withdraw from the study at any time without penalty and without providing a reason, (c) responses would remain anonymous and confidential, (d) participants would receive panel-internal credit points (redeemable for shopping vouchers) through Panel4All for completing the survey, and (e) data would be used solely for academic research purposes. To safeguard confidentiality and data protection, all responses were collected without personally identifying information.

3. Results

3.1. Predicting AI Dependency

The first research question examined how AI literacy, academic self-efficacy, and self-regulated resource management strategies relate to students' reported dependency on AI tools. Bivariate correlations among all study variables are presented in Table 1 and were generally consistent with the multidimensional framework developed in Section 1.6: the skill-based AI literacy dimensions (using/understanding and detecting AI) correlated positively with AI dependency ($r = 0.38$ and 0.19 , respectively, both $p < 0.001$), whereas academic self-efficacy and effort regulation correlated negatively ($r = -0.244$ and -0.290 , both $p < 0.001$). AI self-efficacy and emotional regulation in AI use showed essentially zero zero-order correlations with AI dependency, consistent with the possibility that their effects emerge only when other predictors are controlled. A multiple linear regression analysis was then conducted with AI dependency as the criterion and eight simultaneous predictors: the four AI literacy subscales (using/understanding, detecting, AI self-efficacy, and emotional regulation in AI use), academic self-efficacy, and the three MSLQ resource-management subscales (time and study environment management, effort regulation, and help seeking). Multicollinearity diagnostics indicated no concern (all VIF ≤ 1.87). The overall model was statistically significant, $F(8, 469) = 22.03$, $p < 0.001$, and accounted for 27.3% of the variance in AI dependency ($R^2 = 0.273$; adjusted $R^2 = 0.261$)—a meaningful increase over the 22.1% obtained when AI literacy was modeled as a single aggregate score, indicating that the multidimensional treatment of AI literacy adds explanatory value. The regression coefficients are presented in Table 2.

Within the AI literacy domain, the four subscales operated in theoretically opposing directions, supporting the multidimensional framing developed in Section 1.6. The skill-based dimensions were positively associated with AI dependency: using and understanding AI emerged as the strongest predictor in the model overall ($\beta = 0.404$, $p < 0.001$), and identifying/detecting AI showed a smaller positive association ($\beta = 0.108$, $p = 0.041$). In contrast, AI self-efficacy was negatively associated with AI dependency ($\beta = -0.132$, $p = 0.016$), paralleling the role of academic self-efficacy. Emotional regulation in AI use was not significant ($\beta = -0.035$, $p = 0.435$). Outside the AI literacy domain, the pattern from the original model was replicated: academic self-efficacy was negatively associated with AI dependency ($\beta = -0.197$, $p < 0.001$), effort regulation was negatively associated ($\beta = -0.134$, $p = 0.013$), help seeking was positively associated ($\beta = 0.124$, $p = 0.003$), and time and study environment management was not significant ($\beta = -0.046$, $p = 0.374$). All associations are cross-sectional and correlational. The regression coefficients do not establish causal effects of the predictors on AI dependency.

3.2. Student Profiles of AI Use

To characterize student profiles with respect to AI use, we conducted a K-means cluster analysis on z-standardized scores of AI literacy and AI dependency ($N = 478$). The four-cluster solution yielded clear theoretical differentiation across the AI literacy $\times$ AI dependency plane and was retained as the most interpretable solution. Group sizes were

adequate (all $n \geq 85$) and the between-cluster differences on both constructs were highly significant (AI dependency: $F(3, 474) = 882.25$, $\eta^2 = 0.85$. AI literacy: $F(3, 474) = 239.77$, $\eta^2 = 0.60$). Cluster sizes, means, and standard deviations are presented in Table 3.

The first profile, labeled HL, comprised participants with high AI literacy but relatively low reported dependency, suggesting a more selective and discriminating pattern of AI engagement.

The second profile, labeled MM, comprised participants with moderate levels on both dimensions.

The third profile, labeled LL, comprised participants with relatively low AI literacy and low reported dependency.

The fourth profile, labeled HH, comprised participants with both high AI literacy and high reported AI dependency, suggesting a pattern in which advanced AI competence coincides with heavy reliance on AI tools. Because the present study did not include behavioral measures of AI usage frequency or task type, these profile labels should be interpreted as patterns of self-reported literacy and dependency, not as categories of behavioral AI usage.

3.3. Utilization and Application of Self-Regulated Resource Management Learning Strategies of the Clusters

To examine how the four profiles differ in their utilization of self-regulated resource management strategies and academic self-efficacy, we conducted one-way ANOVAs comparing the four clusters on academic self-efficacy, time and study environment management, effort regulation, and help seeking. Cluster membership served as a four-level between-subjects factor. Effect sizes are reported as eta-squared (η^2), and pairwise comparisons were conducted using Tukey HSD post hoc tests ($\alpha = 0.05$). The results are presented in Table 4. Three of the four comparisons were statistically significant: academic self-efficacy ($F(3, 474) = 22.60$, $p < 0.001$, $\eta^2 = 0.13$), time and study environment management ($F(3, 474) = 11.21$, $p < 0.001$, $\eta^2 = 0.07$), and effort regulation ($F(3, 474) = 19.00$, $p < 0.001$, $\eta^2 = 0.11$). In all three cases, the HL profile (high literacy, low dependency) consistently scored highest, with Tukey HSD post hoc comparisons indicating significantly higher academic self-efficacy than all other profiles, higher time/study management than the HH and MM profiles, and higher effort regulation than the HH and MM profiles. Help seeking did not significantly differ across profiles ($F(3, 474) = 2.01$, $p = 0.112$, $\eta^2 = 0.01$). Because the MSLQ help-seeking subscale captures general academic help seeking from human sources, this null result indicates only that the four profiles do not differ in their general willingness to seek help from peers, instructors, or teaching assistants—not that they differ in AI-specific help seeking, which was not measured in the present study.

4. Discussion

The findings of this study provide a theoretically meaningful contribution to understanding students' engagement with generative AI in higher education. Contrary to the widely held assumption that technological literacy promotes more autonomous learning, the results suggest that AI literacy may also function as a double-edged factor, increasing dependency when not accompanied by strong self-regulatory and motivational resources. It enhances our knowledge regarding students' dependency on AI in higher education, and indicates a complex relationship between AI literacy, academic self-efficacy, learning management strategies, and the level of dependence on AI tools. The analysis of the variables and clusters shows that these factors do not predict dependence in a linear or uniform manner, highlighting that the way AI-based technologies are used in academic contexts depends not only on learners' knowledge and access to the tools, but also on emotional

and behavioral dimensions. We now proceed to discuss the findings related to the three research questions in light of the existing research literature.

4.1. Predicting Students' Reported Dependency on AI Tools

The first research question asked: "How do AI literacy, academic self-efficacy, and self-regulated resource management strategies relate to students' reported dependency on AI tools?" The regression findings suggest that students' self-reported dependency on AI is associated with a combination of cognitive, motivational, and behavioral characteristics. Overall, higher AI literacy, lower academic self-efficacy, weaker effort regulation, and more frequent general academic help seeking were associated with higher reported AI dependency. Because the study is cross-sectional and based on self-report, these associations should be interpreted as patterns of co-occurrence rather than as evidence that any of the predictors causally produces AI dependency. Alternative explanations, including reverse causality, shared method variance, and unmeasured third variables (e.g., academic discipline, prior digital exposure, motivation orientation), cannot be ruled out within the present design.

Disaggregating AI literacy into its four subscales revealed a theoretically meaningful pattern that the single-score analysis obscured. The skill-based dimensions of AI literacy were positively associated with AI dependency, with using and understanding AI emerging as the strongest predictor in the model ($\beta = 0.406$). This finding is consistent with the cognitive-offloading perspective (Risko & Gilbert, 2016) and with technology-adoption frameworks in which competence accelerates rather than restrains use (Venkatesh et al., 2003; Wang et al., 2025). Students who have mastered the practical operation of AI tools have, by definition, expanded the set of academic tasks they can plausibly delegate to AI, and the present data suggest that they do so to a meaningful extent.

In striking contrast, AI self-efficacy students' confidence in their own competence specifically in AI use was negatively associated with AI dependency ($\beta = -0.132$). This pattern mirrors the parallel negative association of academic self-efficacy with AI dependency ($\beta = -0.197$) and supports a unified compensatory account: in line with Bandura's (1997) domain-specific conception of self-efficacy, both general (academic) and domain-specific (AI) self-efficacy beliefs appear to reduce the motivational need to over-rely on AI. Where strong skills enable offloading, strong self-efficacy beliefs appear to buffer against it. Identifying this dual structure within the AI literacy construct is, to our knowledge, novel in the AI-dependency literature and complements recent calls to treat AI literacy as multidimensional rather than as a unitary trait (Carolus et al., 2023; Long & Magerko, 2020).

Educationally, this distinction has important implications. AI literacy curricula that focus narrowly on technical skills (how to prompt, how to use AI tools effectively) may inadvertently increase dependency, whereas curricula that also foster self-efficacy beliefs about AI students' sense that they can think with AI rather than through AI may help protect against overreliance. The same logic applies to academic self-efficacy more broadly: building students' confidence in their own academic capabilities may be at least as protective as teaching them to use AI well.

A positive association also emerged between help seeking and AI dependency. This finding requires particular interpretive caution. The MSLQ help-seeking subscale captures students' general academic help seeking from human sources (peers, instructors, teaching assistants). It does not measure help seeking from AI tools (Pintrich et al., 1993; Karabenick & Newman, 2006). Consequently, the present results cannot support the inference that students are specifically substituting AI for human helpers. A plausible alternative interpretation is that students who are generally more inclined to seek academic support, whether from peers, instructors, or other sources may also be more open to incorporating AI tools into their

broader help-seeking repertoire. Whether this constitutes adaptive instrumental help seeking, in which AI complements human support, or executive help seeking, in which AI delivers ready-made solutions that substitute for cognitive effort (Karabenick & Newman, 2006), cannot be determined from the present measure. Future research incorporating AI-specific help-seeking instruments is needed to disentangle these possibilities.

The insignificance of time and environment management skills raises an interesting interpretive perspective. Firstly, other variables in the model demonstrated stronger statistical significance, suggesting that time and environment management skills may not be among the primary factors predicting AI dependency. Second, it is possible that the statistical test did not sufficiently distinguish between learners who manage their time effectively as part of genuine self-regulation management skills, and those who seek to complete tasks as quickly as possible with minimal effort, often relying on shortcuts such as AI to achieve this goal. Unregulated media behavior was previously found to be clearly related to inadequate self-regulation processes such as difficulties with time restrictions, a sense of losing control, and improper self-evaluation of usage duration (see Meier et al., 2016).

This finding raises the question of whether basic organizational skills are relevant predictors of AI dependency. Alternatively, in a rapidly evolving technological learning environment, emotional and motivational variables, such as AI literacy, self-efficacy, and effort regulation, may play a more dominant role in shaping patterns of AI use than logistical or environmental organization. Organizing and managing time are only partial aspects of self-regulation, related to technical skills. AI dependency, as found in this study, is more related to emotional aspects and the ensuing behaviors.

4.2. AI Literacy and Dependency Profiles

The second research question was: “What student profiles emerge when considering levels of AI literacy and AI dependency, and how do these relate to learning behaviors?”. Although it may be assumed that higher levels of AI knowledge would naturally correspond to greater dependency on AI tools, the findings suggest a more nuanced pattern involving two contrasting profiles. The HH profile (HH: high literacy–high dependency) represents participants characterized by both high AI literacy and high reported dependency on AI tools. This profile may reflect students who integrate AI extensively into their academic learning practices. In contrast, the HL profile (HL: high literacy–low dependency) includes participants with similarly high levels of AI literacy but relatively low reported dependency. This pattern reflects a more selective and potentially more self-regulated approach in which students demonstrate familiarity with AI tools without relying on them extensively.

The contrast between these two profiles suggests that higher AI literacy does not necessarily correspond to greater dependency. Rather, technological knowledge may also support more deliberate and restrained patterns of use. The MM profile (MM: moderate literacy–moderate dependency) is characterized by moderate levels of both AI literacy and dependency. This group may represent students in an intermediate stage of engagement with AI technologies. The LL profile (LL: low literacy–low dependency) comprises participants characterized by relatively low AI literacy and low reported dependency, suggesting limited engagement with AI tools. Possible explanations for this pattern may include limited exposure or training, hesitation toward AI technologies, or perceptions that such tools are not relevant to current academic needs.

Because the study relied on self-report measures rather than direct behavioral indicators of AI use frequency or task type, the profiles should be interpreted as reflecting perceived patterns of literacy and dependency rather than objective categories of AI users. Nevertheless, the findings may suggest the potential value of considering differentiated approaches to AI training and implementation.

For example, students in the HH profile may benefit from greater emphasis on critical thinking, ethical awareness, and reflective boundaries of use, whereas students in the MM profile may benefit from guided skill development and support for more intentional engagement with AI tools. The LL profile may require foundational exposure and opportunities for gradual experimentation with AI technologies. Finally, students in the HL profile may demonstrate characteristics associated with more autonomous and self-regulated engagement with AI tools.

Overall, the findings highlight the heterogeneity of students' relationships with AI technologies and suggest that AI literacy and AI dependency may combine in multiple ways rather than representing a single continuum. These profiles may contribute to a more nuanced understanding of how students engage with AI in academic settings and may support future research and educational planning in this area.

4.3. AI Literacy, Dependency and Resource Management Learning Strategies

The third research question was "In what ways do these clusters differ in their utilization and application of self-regulated resource management learning strategies?" To deepen the understanding of students' emotional aspects and learning behaviors, the four profiles were compared on measures of learning-management strategies and academic self-efficacy. The findings related to the third research question indicate clear and meaningful differences among the identified profiles in their utilization of self-regulated resource management learning strategies. Specifically, students with high AI literacy and low dependency (HL) demonstrated the most adaptive pattern of resource management strategies. This group exhibited significantly higher levels of academic self-efficacy, more effective time and environment management, and stronger effort regulation compared to the other clusters. These results suggest that students who possess strong AI literacy while maintaining low dependency on AI are better able to regulate their learning processes and manage cognitive, temporal, and motivational resources independently.

In contrast, clusters characterized by moderate or high levels of AI dependency showed weaker performance across key resource management dimensions, despite varying levels of AI literacy. The high-literacy, high-dependence group, for example, does not lead in self-management measures and was even found to be lower than other groups. Despite their technical knowledge, high dependence may undermine learner autonomy, reduce cognitive effort, and even create an illusion of competence. This pattern indicates that reliance on AI may undermine students' engagement in active self-regulation processes, such as sustained effort and strategic time management. Notably, no significant differences were found between profiles in help-seeking behavior, suggesting that the observed disparities are not attributable to differences in students' willingness to seek external support, but rather to variations in internal self-regulatory capacities. Overall, these findings underscore that effective utilization of self-regulated resource management strategies is closely associated with autonomous and controlled use of AI, rather than with AI literacy alone. The results highlight the importance of fostering learners' ability to integrate AI as a supportive tool while preserving personal agency and responsibility in managing their learning resources.

Educational implications should be drawn cautiously, as the present study is cross-sectional, self-report-based, and does not directly test any intervention. With these caveats in mind, the patterns observed may suggest that academic programs could benefit from training that explains how generative AI systems operate, addresses their limitations and biases, and develops critical prompting and evaluation skills, ideally through practical, workshop-based formats. Because students who reported higher AI dependency also reported weaker self-regulation, instructional designs that scaffold time management, effort regulation, and reflective engagement with AI outputs may be especially valuable. Strengthening academic

confidence and self-awareness may further encourage learners to use AI as a supportive resource rather than a substitute for independent thought. We frame these as tentative implications for educational practice and as hypotheses for future intervention research, rather than as evidence-based prescriptions established by the present study.

Both intermediate groups (medium-medium and low-low) do not lead in self-management and self-efficacy measures and were found to score lower than the other groups in time management, persistence, and perceived competence. It is possible that these groups have not yet developed awareness of when the tool serves as a substitute and when it is merely supportive. The students are familiar with the technology but have not yet developed a conscious strategy, using it instead in an intuitive manner. The ability exists, but the control is lacking: When is it appropriate to use AI? When should its reliability be questioned? Is it right or advisable to rely on it? Is it suitable for one task or another? They may understand that AI can assist them, yet remain hesitant and at times frustrated.

Regarding help seeking, no significant differences were found. All groups reported similar behavior in seeking assistance, suggesting that AI dependence or literacy does not influence the tendency to request human guidance. Learners may prefer AI for knowledge-based tasks, yet still turn to human sources for emotional, motivational, or social support.

Assessment methods should be adapted to an AI-rich environment by emphasizing thinking, analysis, metacognition, and judgment, and by incorporating elements such as process documentation, reflective dialogue, or critique of AI-generated outputs. Learners characterized by high reported dependency on AI tools may particularly benefit from support aimed at strengthening self-regulation and reflective engagement with AI use.

Taken together, the findings indicate that the impact of artificial intelligence on learning processes cannot be understood in purely technological terms, but requires a broader examination of behavioral patterns, emotional regulation, and self-regulated learning. The differences identified among learner profiles primarily reflect disparities in self-control, academic self-efficacy, persistence, and the management of learning resources, rather than differences in technological knowledge or access to AI tools. These findings underscore that AI functions as an effective supportive resource only when embedded within a framework of emotional-behavioral skills that enable conscious, critical, and autonomous use. Accordingly, the central contribution of this study lies in shifting the focus from a technological-instrumental conception of AI literacy toward a pedagogical, behavioral, and emotional perspective that highlights the role of self-regulation, self-awareness, and learner responsibility in shaping adaptive learning experiences in an AI-rich educational context.

4.4. Limitations

Several additional limitations should be acknowledged. First, recruitment through a commercial online panel may introduce selection biases relative to the broader population of Israeli higher education students: panel members may differ in technological engagement, motivation to complete surveys, and demographic composition. The findings may therefore not generalize to non-panel populations or to students in other national higher education systems. Second, all study variables were collected at a single time point using self-report instruments, creating the potential for common-method bias to inflate the observed associations. Although attention checks and quality-control procedures were applied, no procedural or statistical remedies (e.g., temporal separation of predictors and criterion, marker variables, Harman's single-factor test) were implemented in the present design. Third, the study did not differentiate among academic disciplines or years of study, and field-specific patterns in AI engagement may therefore have been obscured. Fourth, no direct behavioral indicators of AI use (e.g., frequency of AI use, types of tasks delegated to AI, time spent interacting with AI tools) were collected. Consequently, the dependency

construct reflects students' self-perceptions rather than objective behavioral patterns. Fifth, although AI literacy was analyzed as a unidimensional aggregate score, the MAILS instrument captures four conceptually distinct components, and the four dimensions may relate differently to AI dependency. Future research should examine these dimensions separately. Sixth, the regression model accounted for 27.3% of the variance in AI dependency, leaving a substantial proportion unexplained, a reminder that AI dependency is likely shaped by additional factors beyond those examined here, including personality traits, prior digital habits, instructional context, and broader cultural attitudes toward technology.

The integration of quantitative and qualitative approaches may enrich existing knowledge and provide a more nuanced, comprehensive, and context-sensitive understanding of the relationships between AI, motivation, emotions, and academic learning. In addition, future intervention studies examining the effects of AI-based courses, workshops, or instructional tools on students' self-efficacy, motivation, technological literacy, and self-regulated learning may contribute to the development of evidence-based educational models.

5. Conclusions

The findings of this study extend the existing theoretical framework regarding the factors influencing the use of AI. While previous studies have established relationships between well-known learning components such as self-efficacy and executive functions as part of the interplay underlying the use of artificial intelligence and academic literacy (Bandura, 1986; Pajares, 2002; Southworth et al., 2023; Zimmerman, 2000), the present study highlights the role of emotional and behavioral components as well as AI literacy.

The data show that there is no single way of using AI among students. Four clear profiles emerged, differing in their combinations of AI literacy and AI dependency, and these profiles also differed in self-efficacy and resource management strategies. This heterogeneity implies that no single instructional strategy fits all learners. Rather, frameworks for learning, support, and guidance must be adjusted to user characteristics, ranging from foundational AI skills for novice users to critical and reflective use among those already skilled. Such adjustments should integrate emotional-behavioral content (self-evaluation, self-reflection, and self-regulation) alongside technological training.

The findings indicate that the relation between AI and usage patterns is complex rather than linear and is affected by preferences, approaches, and reflective ability—emotional and behavioral aspects and not only cognitive. In order to promote the rational integration of AI in the academy, flexible instructional programs are required, based on user profiles, that promote critical and ethical thinking, as well as technological proficiency.

In sum, the present study supports a key takeaway for higher-education research and practice: AI literacy alone does not guarantee autonomous or self-regulated AI use, and academic self-efficacy together with self-regulated learning practices appears to be central to how students engage with AI tools. Given the cross-sectional and self-report nature of the data, these findings are best read as a basis for further longitudinal, behavioral, and intervention research, not as evidence for specific causal or prescriptive claims.

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