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Analysis of the Connection: Emotional Regulation and Social Skills in Shaping Study Habits through Cognitive Engagement in the Era of AI-Based Economic Learning

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Abstract

The rapid growth of Artificial Intelligence has transformed learning behavior in higher education, raising concerns about students' cognitive engagement when relying on AI-generated assistance. This study examines how emotion regulation and social skills influence students' study habits in AI-based economic learning, with cognitive engagement as a mediating variable. Using an explanatory quantitative design, data were collected from undergraduate students of the Faculty of Economics and Business at accredited public universities in East java, Indonesia, through a validated questionnaire consisting of 27 items adapted from established measurement scales. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that emotion regulation and social skills have a positive direct effect on students' study habits. However, only social skills indirectly enhance study habits through increased cognitive engagement, while emotion regulation does not significantly influence cognitive engagement in AI-assisted learning. These results highlight that interpersonal competence plays a critical role in sustaining cognitive engagement and developing effective study habits, even as learning becomes increasingly supported by AI. Practically, the study suggests that higher education institutions and policymakers should design learning programs that integrate emotional management, social skill development, and responsible AI use to foster adaptive learning behavior. The novelty of this study lies in revealing distinct psychological mechanisms underlying study habits in AI-based economic learning, a context that remains underexplored in Indonesia.

How to Cite

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INTRODUCTION

The rapid development of digital technology has brought significant changes to the world of education. Artificial intelligence (AI) technology has opened up new opportunities in everyday life, from information technology and healthcare to education (Karim et al., 2025). This transformation is increasingly evident with the advent of artificial intelligence (AI), which is now widely adopted in various fields, including education. AI offers great opportunities to improve the quality of learning through faster access to information, more personalized feedback, and support for a more efficient learning process.

Students in higher education are one of the groups that make the most use of AI-based technology. In a global context, according to Chegg's Global Student Survey (Yonatan, 2025) four out of five students worldwide have used AI to support their learning process, and only 20% have never used it. Interestingly, out of the 15 countries surveyed, Indonesia is recorded as the country with the highest percentage of students using AI in learning, at 95%. Most Indonesian students use AI to complete academic assignments (86%), develop career plans (52%), and even help manage their personal schedules (33%). The high intensity of AI usage indicates that AI has become an integral part of students' learning habits.

However, the use of AI does not always have the same impact on every student. In a study (Liang et al., 2023) student interaction with Generative AI was positively associated with learning achievement, with self-efficacy and cognitive engagement acting as mediators. Some students feel that AI helps them because it increases their cognitive engagement in understanding concepts and material. However, behind this convenience, uncontrolled use of AI raises new issues. A number of studies show that dependence on AI can reduce cognitive engagement and critical thinking skills, as well as weaken students' learning habits Students tend to accept answers from AI without conducting a thorough evaluation and elaboration process, resulting in superficial and instant learning activities. This condition has a direct impact on study habits, such as a decline in learning consistency, low independent effort, and reduced academic reflection. Findings by Berliana & Cahya, (2024) also show that excessive use of AI can reduce student cooperation and social interaction, as discussions and collaboration among students are increasingly replaced by AI as a task solver.

In Bandura's Social Cognitive Theory (Bandura, 1986, 2001) learning behavior is the result of reciprocal interactions between personal factors, behavior, and the environment. In this study, emotion regulation and social skills are positioned as personal factors that influence how students respond to AI-based learning environments and form study habits. According to (C. Li et al., 2009) emotion regulation refers to the ability to control one's own emotional state, as well as the process by which individuals regulate the emergence, experience, and expression of emotions. Emotion regulation plays an important role in determining how students utilize technology, including artificial intelligence. Previous research confirms that emotion regulation affects an individual's ability to adapt socially and interact with AI-based educational technology, thereby supporting the process of emotional socialization in the digital age (Ma et al., 2025). Hou et al., (2025) found that the increased use of generative AI in the learning process has shifted the way students seek help, where questions that were usually directed to friends are now redirected to AI. These changes reduce interaction between students and even cause feelings of isolation and demotivation as the existing social support system weakens. This shows that students with low emotional regulation skills tend to use AI as an escape when stressed, while weak social skills encourage students to replace academic interaction with AI.

The impact of emotion regulation and social skills is closely related to study habits. Study habits are not just learning routines, but include how students manage their time, utilize learning resources, and complete academic assignments. As support, a study by (Iqbal et al., 2022) found that emotional intelligence, including emotion regulation and social skills, positively affects cognitive engagement, which in turn improves students' study habits. Students with good emotion regulation and social skills are expected to be able to form more productive study habits when using AI.

In this context, the role of cognitive engagement becomes very important as a mediating variable. Cognitive engagement is understood as an internal process that bridges the influence of personal factors on learning behavior. Based on constructivist theory (Piaget & Inhelder, 1969; Vygotsky & Cole, 1978) meaningful learning requires students to be actively involved in processing, reflecting on, and constructing knowledge through social interaction. Cognitive engagement refers to the extent to which students actively use motivation and learning strategies in their learning process (Richardson & Newby, 2006), including the effort they exert and their persistence in facing challenging tasks (Rotgans & Schmidt, 2011). When AI is used without adequate emotion regulation and social skills, students tend to learn passively, resulting in decreased cognitive engagement and weakened study habits. Thus, cognitive engagement acts as an indirect mechanism that explains how emotion regulation and social skills influence students' study habits in the AI era.

Unfortunately, studies linking emotion regulation, social skills, cognitive engagement, and study habits of students in the use of AI, particularly in economics learning, are still limited. Most previous studies have focused more on the impact of technology or AI on learning outcomes in general, without considering the psychosocial factors of students that play an important role in the effectiveness of AI-based learning (Chan & Hu, 2023; Indonesia, 2022; Kasneci et al., 2023; Liang et al., 2023; Zhai et al., 2024). This is in line with the findings (Vistorte et al., 2024) which confirm that although research related to the use of AI to evaluate emotions in learning continues to grow, there are still few studies that comprehensively examine the relationship between emotional aspects and learning outcomes such as study habits. This condition creates an important research gap that needs to be addressed.

This research is important because students' study habits in the era of AI utilization will determine the success of the educational process. If emotion regulation and social skills are not managed properly, the use of AI can reduce cognitive engagement and study habits. Conversely, if these two factors are strong, AI can be a strategic tool in building cognitive engagement and strengthening effective study habits.

This study aims to analyze the influence of emotion regulation and social skills on college students' study habits, with cognitive engagement as a mediating variable. This study focuses not only on the direct influence of emotion regulation and social skills, but also on how cognitive engagement strengthens this relationship. Although a number of previous studies have examined psychological factors in learning, studies that specifically integrate emotion regulation, social skills, and cognitive engagement with student study habits in Indonesia are still limited. Therefore, this study is important to provide a more comprehensive analysis in the field of education.

Theoretically, this study is expected to enrich the development of educational science by emphasizing the role of psychological factors and cognitive involvement in building student learning habits. In practical terms, the results of this study can provide insights for students, educators, and educational institutions in designing strategies and programs that support emotion management, social skills strengthening, and increased cognitive engagement in the learning process. The hypotheses in this study were formulated based on the theoretical framework and previous research results. For clarity, the research hypotheses are presented in Table 1.

Tabel 1. Research hypothesis

Hypothesis
H1: Emotion regulation (ER) has a positive effect on study habits (SH).
H2: Social skills (SS) have a positive effect on study habits (SH).
H3: Emotion regulation (ER) has a positive effect on cognitive engagement (CE)
H4: Social skills (SS) have a positive effect on cognitive engagement (CE).
H5: Cognitive engagement (CE) has a positive effect on study habits (SH).
H6: Cognitive engagement (CE) mediates the relationship between emotion regulation (ER) and study habits (SH).
H7: Cognitive engagement (CE) mediates the relationship between social skills (SS) and study habits (SH).

Source: Processed Primary Data (2025)

METHODS

This study employed an explanatory quantitative design to examine the relationships among emotion regulation, social skills, cognitive engagement, and study habits in AI based economic learning. The population consisted of students from the the Faculty of Economics and Business enrolled in economics courses at state universities with excellent accreditation in East Java, Indonesia. Convenience sampling was employed because the study required respondents who were actively engaged in AI-assisted learning activities and willing to provide information regarding their learning behavior in digital learning environments (Etikan et al., 2016). A total of 197 undergraduate students participated in this study, which met the recommended sample adequacy criteria for Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis (Chin, 1998; J. F. Hair et al., 2017; Kock & Hadaya, 2016).

Data were collected online using Google Forms through a questionnaire consisting of 27 items measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instrument was adapted from established scales, including emotion regulation from (Gross & John, 2003), social skills adapted from (Gresham & Elliott, 1990), cognitive engagement adapted from Goodenow (1993) in (Appleton et al., 2006), and the study habits instrument was adapted from the Palsane and Sharma Study Habits Inventory (PHSSI) developed by M. N. Palsane and Saddhna Sharma(Tus et al., 2020). The research model is illustrated in Figure 1.

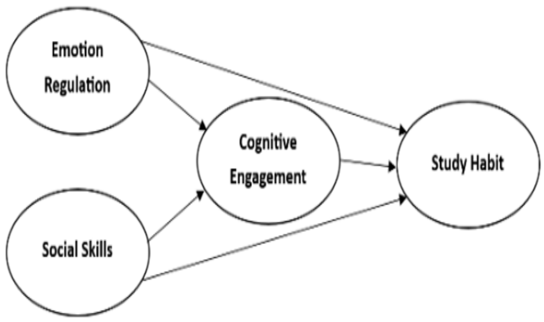

Figure 1. Research Model

Before the main survey, a pilot test involving 40 respondents was conducted to evaluate instrument validity and reliability using SPSS Statistics 26. Validity testing ensured that each indicator appropriately measured the intended construct, while reliability was assessed using Cronbach's Alpha to examine internal consistency (Ghozali, 2018). Data that met the validity and reliability criteria were then analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of SmartPLS 4 software. The PLS-SEM method was chosen because it is suitable for predictive research, involves latent variables, and uses many indicators in the research model. (J. F. Hair et al., 2021). The analysis stages were carried out through: (1) testing the measurement model (outer model), (2) demographic analysis, (3) testing the structural model (inner model).

RESULTS AND DISCUSSION

Demographic Analysis of Respondents

Demographic analysis was conducted to describe the characteristics of respondents and to provide context for students' learning behavior in AI-based economic learning. A total of 197 valid student responses from the Faculty of Economics and Business at accredited public universities in East Java were included in the final analysis (see Table 2). Most respondents were female (78.2%), while male students accounted for 21.8%. Based on the year of entry the majority of respondents came from the 2022 class (51.3%), indicating that most participants had sufficient experience in university learning and were already familiar with digital learning systems. In terms of AI utilization in learning activities, ChatGPT (78.7%) was the most frequently used AI to assist in the learning process, with 44.2% of respondents using it every day. This illustrates that the use of AI has become part of students' academic routines in the era of digital economy learning.

In the context of economics learning, students are generally required to analyze cases, solve problems, interpret data, and understand theoretical concepts. These learning activities require not only independent learning skills but also discussion, collaboration, and active cognitive involvement. However, the intensive use of AI may encourage students to rely on instant answers, which can reduce critical thinking and deep learning processes. Therefore, the demographic profile of respondents strengthens the relevance of this study in examining the roles of emotion regulation, social skills, cognitive engagement, and study habits in AI-assisted learning.

Table 2. Demographic Characteristics of Respondents

Category	Indicator	Number	Percentage
Gender	Women	154	78.2
	Men	43	21.8
Generation	2021	2	1.0
	2022	101	51.3
	2023	39	19.8
	2024	53	26.9
	2025	2	1.0
Most Frequently Used AI	ChatGPT	155	78.7
	Gemini	15	7.6
	Perplexity AI	14	7.1
	Claude AI	6	3.0
	Others	7	3.6
Frequency of AI Use	Every day	87	44.2
	3-4 times/week	72	36.5
	1-2 times/week	29	14.7
	Rarely	9	4.6

Source: Processed Primary Data (2025)

Outer Model

Convergent Validity

Convergent validity is used to see the extent to which indicators are able to reflect the latent variables being measured. This test is evaluated based on the outer loading value, where indicators are considered valid if they have a value of ≥ 0.70 (Chin, 1998; J. F. Hair et al., 2017). However, indicators with values between 0.40 and 0.70 can still be retained if supported by AVE values ≥ 0.50 and Composite Reliability ≥ 0.70 (J. Hair & Alamer, 2022). More detailed outer loading values can be seen in Table 3.

Table 3. Convergent Validity Test Results

Variable	Indicator	Outer Loading	Description
Emotion Regulation	X1.1	0.833	Valid
	X1.2	0.636	
	X1.3	0.685	
	X1.4	0.654	
Social Skills	X2.1	0.656	Valid
	X2.2	0.621	
	X2.3	0.604	
	X2.4	0.695	
	X2.5	0.673	
	X2.6	0.757	
	X2.7	0.726	
	X2.8	0.677	
Cognitive Engagement	Z1.1	0.776	Valid
	Z1.2	0.771	
	Z1.3	0.716	
	Z1.4	0.701	
	Z1.5	0.767	
Study Habits	Y1.1	0.664	Valid
	Y1.2	0.665	
	Y1.3	0.724	
	Y1.4	0.659	
	Y1.5	0.621	
	Y1.6	0.749	
	Y1.7	0.636	
	Y1.8	0.632	
	Y1.9	0.608	
	Y1.10	0.610	

Abbreviations: ER, emotional regulation; SS, social skills; CE, cognitive engagement; SH, study habits

Source: Processed Primary Data (2025)

Based on Table 3, all indicators have outer loading values above 0.60, thus meeting the minimum criteria for convergent validity. Furthermore, the test results show that all constructs have Composite Reliability values ≥ 0.70, indicating good internal consistency. Although the AVE values (Table 4) for the Emotion Regulation, Social Skills, and Study Habits constructs are slightly below 0.50, this condition is still acceptable because it is supported by high construct reliability.

Thus, it can be concluded that the measurement model in this study has met the convergent validity criteria and is suitable for use in further analysis.

Construct Validity and Reliability

In addition to testing convergent validity through outer loading, this study also evaluated construct reliability. This test was conducted to ensure that the research instrument was consistent and that the indicators adequately reflected the construct. Based on the Cronbach's alpha results in Table 4, all variables obtained a Cronbach's alpha value above 0.70, indicating adequate reliability (Purwanto & Sudargini, 2021). Furthermore, rho_A is also calculated as an alternative measurement of reliability that is more accurate in PLS-SEM (J. F. Hair et al., 2021). The results show that all constructs have adequate internal reliability, as all values are above the minimum threshold of 0.70. Composite reliability is recommended to be at least 0.60 to indicate high reliability (Purwanto & Sudargini, 2021). The results show that all constructs have high and consistent reliability, supporting the validity of the instrument measurements.

Table 4. Results of construct reliability testing

	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Cognitive Engagement (Z)	0.801	0.803	0.863	0.558
Emotion Regulation (X1)	0.734	0.892	0.797	0.499
Social Skill (X2)	0.831	0.835	0.871	0.459
Study Habit (Y)	0.855	0.864	0.884	0.433

Source: Processed Primary Data (2025)

Discriminant Validity

Discriminant validity can be measured through the HTMT ratio (Iqbal et al., 2022). Researchers (Henseler et al., 2015; Liao, 2025) using HTMT to measure discriminant validity for reflective scales in research. Discriminant validity is used to ensure that each construct in the research model is clearly distinct from one another and does not overlap. In this study, discriminant validity was tested using two approaches, namely the Fonell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT). Both methods are recommended procedures in PLS-SEM analysis.

Table 5. Discriminant validity Fornell Larcker Criterion

	Cognitive Engagement	Emotion Regulation	Social Skill	Study Habit	Description
Cognitive Engagement	0.747				Valid
Emotion Regulation	0.275	0.706			Valid
Social Skill	0.558	0.421	0.678		Valid
Study Habit	0.586	0.381	0.559	0.658	Valid

Source: Processed Primary Data (2025)

The Fornell and Larcker criteria are that the square root of AVE is greater than the correlation between constructs (Fornell & Larcker, 1981). The results in Table 5 show that the CE variable has a higher EVE root (0.747) correlation than RE (0.275), SS (0.558), and SH (0.586). The same results were also obtained in other variables. Thus, it can be concluded that the measurement items have good validity based on the Fornell and Larcker method. The recommended discriminant validity criterion for HTMT is no more than 0.90 (Henseler et al., 2015). Results in Table 6. The HTMT values for all constructs are below 0.90. This indicates that each construct has clear differences from one another.

Table 6. Discriminant validity of HTMT

	Cognitive Engagement	Emotion Regulation	Social Skill	Study Habit
Cognitive Engagement				
Emotion Regulation	0.247			
Social Skill	0.677	0.438		
Study Habit	0.681	0.393	0.647	

Source: Processed Primary Data (2025)

Goodness of Fit Model

Model feasibility testing was conducted to ensure that the PLS-SEM model used was feasible for further analysis. The model feasibility indicators used included SRMR and NFI. Based on the results in Table 7, the SRMR value of 0.081 is still within acceptable limits because it is less than the model is considered to have sufficient goodness of fit. The NFI value of 0.646 is still in the acceptable category, although it has not reached the ideal value >0.90 (Bentler & Bonett, 1980; Hu & Bentler, 1998). Therefore, the model in this study is considered feasible and can be continued to the inner model testing stage.

Table 7. Model Fit

Indeks	Estimated Model
SRMR	0.081
NFI	0.646

Source: Processed Primary Data (2025)

Inner Model

The coefficient of determination (R2) is used to see the ability of independent variables in explaining dependent variables. The threshold values for R2 are 0.25, 0.50, and 0.750, which are considered to have weak, moderate, and strong explanatory power, respectively(Huang, 2021). Table 8 shows that the R-square value used for the cognitive engagement variable is 0.313 (31.3%). This indicates that emotion regulation and social skills contribute 31.3% to cognitive engagement, while the remaining 68.7% is explained by other variables not included in this study. The R-square value for the study habits variable is 0.442 (44.2%). This indicates that emotion regulation, social skills, and cognitive engagement contribute 44.2% to study habits, while the remaining 55.8% is contributed by other variables not discussed in this study. Thus, both models have explanatory power in the moderate category, indicating that the models are adequate for predicting endogenous variables. The Q-Square predictive relevance (Q2) value shown in Table 7 is 0.617 (61.7%), indicating that emotion regulation, social skills, and cognitive engagement contribute 61.7% to study habits as a whole. The remaining 38.3% is explained by other variables not included in the study.

Table 8. R-squared table

	R Square	R Square Adjusted
Cognitive Engagement	0.313	0.306
Study Habit	0.442	0.434
$Q^2 = 1 - [(1 - R_1^2)(1 - R_2^2)]$		
$Q^2 = 1 - [(1 - 0.313)(1 - 0.442)] = 0.617$		

Source: Processed Primary Data (2025)

Partial Hypothesis Testing

Hypothesis testing is conducted by examining the direct influence between variables in the structural model. The decision to accept a hypothesis is based on a p-value <0.05. The results of the direct effect testing are presented in Table 9.

Table 9. Direct relationship

Direct Relationship	Coefficients	t-statistic	P Values	Results
ER -> SH	0.158	2.305	0.000	Accepted
SS -> SH	0.276	3.570	0.000	Accepted
ER -> CE	0.049	0.716	0.474	Rejected
SS -> CE	0.537	9.539	0.000	Accepted
CE-> SH	0.389	5.606	0.000	Accepted

Abbreviations: ER, emotion regulation; SS, social skills; CE, cognitive engagement; SH, study habits

Source: Processed Primary Data (2025)

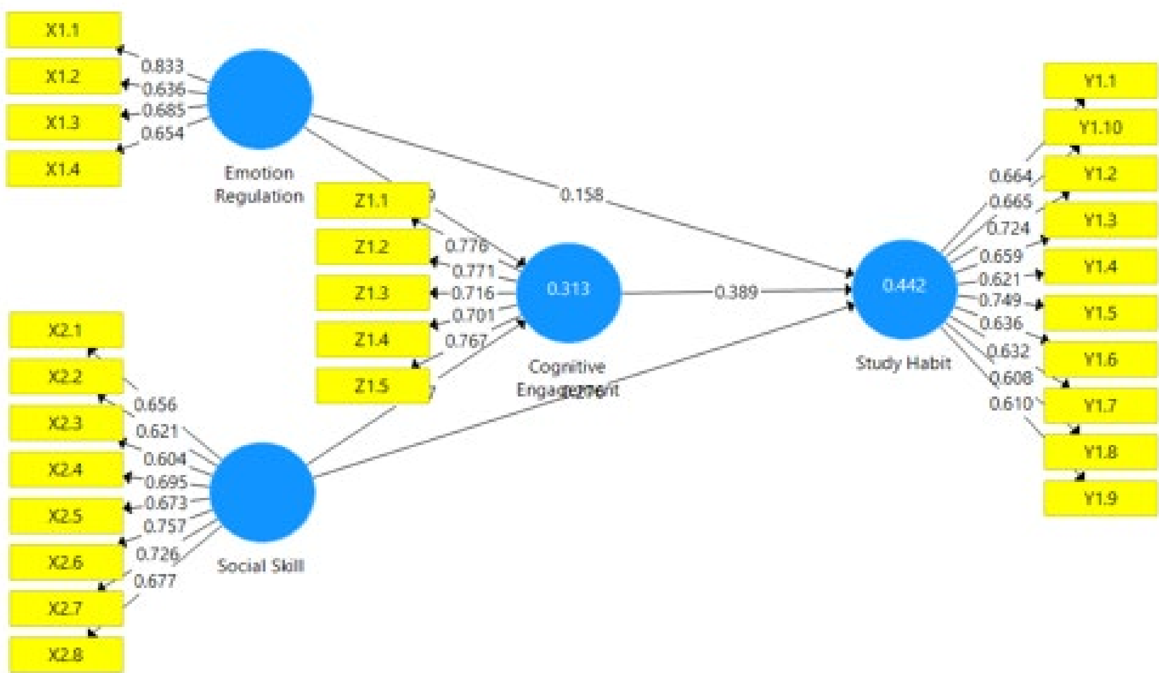

Figure 2. Path analysis model

Based on Table 9, social skills showed the strongest influence on cognitive engagement (β=0.537; p<0.001), while emotion regulation did not significantly affect cognitive engagement (β=0.049; p=0.474). In addition, emotion regulation, social skills, and cognitive engagement each had a positive effect on study habits. These findings indicate that students' learning habits in AI based learning environments are influenced not only by emotional control but also by their ability to interact socially and engage cognitively in the learning process.

Mediation Test

Mediation tests were conducted to examine the role of cognitive engagement in mediating the relationship between emotion regulation and social skills on study habits. The results of the indirect effect tests are presented in Table 10.

As shown in Table 10, cognitive engagement failed to mediate the relationship between emotion regulation and study habits. In contrast, cognitive engagement partially mediated the relationship between social skills and study habits. These findings indicate that social skills influence study habits both directly and indirectly through increased cognitive engagement.

Table 10. Indirect relationship

Indirect Relationship	Coefficients	t-statistic	P Values	Results
ER -> CE -> SH	0.019	0.698	0.496	Rejected
SS -> CE-> SH	0.209	4.666	0.000	Accepted

Abbreviations: ER, emotion regulation; SS, social skills; CE, cognitive engagement; SH, study habits

Source: Processed Primary Data (2025)

The findings of this study demonstrate that emotion regulation and social skills both contribute significantly to the study habits of university students in AI based learning contexts. However, the mechanisms underlying these relationships differ. Social skills influence study habits both directly and indirectly through cognitive engagement, indicating a partial mediating effect. In contrast, emotion regulation directly affects study habits but does not significantly influence cognitive engagement, resulting in the absence of a mediating effect.

The significant influence of emotion regulation on study habits suggests that students who are able to manage stress, anxiety, and academic pressure tend to maintain more structured and consistent learning routines, even when learning activities heavily involve AI technologies. In this study, study habits in AI based learning refer not only to traditional learning discipline, but also to how students manage AI use responsibly, organize study schedules, evaluate AI generated information, and maintain independent learning routines despite the availability of instant answers. Students with good emotional regulation tend to use AI more adaptively, preventing excessive dependence on AI generated assistance. This finding is consistent with Gross (2015), who explains that emotion regulation supports adaptive behavior through self regulation processes. Recent studies also emphasize that students with better emotion regulation demonstrate stronger academic persistence, learning adaptability, and resilience in challenging learning situations (Heydarnejad et al., 2022; Peng & Zhou, 2025). Furthermore, Manalu et al. (2025) found that emotion regulation contributes to the development of more structured academic habits and learning skills among university students.

Nevertheless, the results reveal that emotion regulation does not significantly influence cognitive engagement. This finding indicates that emotional stability alone is insufficient to encourage deep cognitive involvement in AI assisted learning activities. In AI based learning environments, learners may feel emotionally stable while simultaneously relying on AI generated responses that reduce cognitive effort. The convenience of obtaining summaries, explanations, and direct answers from AI systems potentially decreases the tendency to analyze information critically or engage in deeper reflective thinking(Kasneci et al., 2023; Tlili et al., 2023; Zhai et al., 2024). Thus, AI based study habits may produce both positive and negative consequences. On one hand, AI can improve learning efficiency, accessibility, and academic support; on the other hand, excessive reliance on AI may weaken deep learning processes and reduce cognitive effort may weaken deep learning processes and reduce cognitive effort(Chan & Hu, 2023). This result aligns with Kim & Pekrun (2014), who argue that cognitive engagement is more strongly influenced by intrinsic motivation and active learning strategies than by emotional regulation itself. Similarly, Rentzios et al. (2025) explain that emotion regulation is more closely associated with academic motivation and learning approaches rather than directly determining the depth of cognitive processing. Recent discussions regarding AI supported learning also suggest that AI technologies may reduce cognitive effort because learners can obtain information instantly without engaging in deeper analytical processes (Zhai et al., 2024).

The absence of a mediating effect of cognitive engagement on the relationship between emotion regulation and study habits further strengthens the argument that emotion regulation primarily functions as a mechanism for maintaining behavioral stability rather than encouraging cognitive depth. In this study, cognitive engagement acts neither as a full nor partial mediator because the indirect effect between emotion regulation and study habits was not significant. Therefore, individuals who are able to regulate emotions effectively may still maintain study discipline, learning consistency, and AI supported academic routines, but this does not necessarily mean they cognitively process learning materials in a deeper or more reflective manner. In contrast, social skills demonstrate a more comprehensive role in shaping study habits in AI supported learning environments. The findings show that social skills significantly influence both cognitive engagement and study habits. Moreover, cognitive engagement partially mediates the relationship between social skills and study habits, meaning that individuals with stronger social competence are more likely to develop effective learning habits through increased cognitive involvement. This finding supports Social Constructivism theory proposed by Vygotsky & Cole (1978), which emphasizes that learning occurs through interaction, collaboration, and social participation.

Individuals with strong social skills tend to engage more actively in discussions, collaborative problem solving, peer feedback, and knowledge sharing, including when using AI technologies. In the context of AI based learning, learners with better interpersonal competence are more likely to use AI as a collaborative learning partner rather than merely as a tool for obtaining instant answers. They tend to verify AI generated information through discussion, compare perspectives with peers, and use AI outputs as materials for reflection and collaborative analysis. As a result, AI use becomes part of an active learning process rather than passive information consumption. These findings are consistent with recent studies showing that social interaction enhances active participation, critical thinking, and deeper cognitive engagement in digital learning environments (Hou et al., 2025; Liang et al., 2023). Furthermore, individuals with stronger social competence tend to possess better academic confidence and support networks, which subsequently increase engagement in learning processes (Y. Li & Lerner, 2011).

The significant influence of cognitive engagement on study habits further confirms that individuals who actively invest effort in understanding, analyzing, and reflecting on learning materials are more likely to develop structured and reflective learning routines. This finding aligns with previous studies emphasizing that cognitive engagement plays an important role in shaping learning behavior and learning persistence (Richardson & Newby, 2006; Rotgans & Schmidt, 2011). In active learning contexts, engaged learners also tend to regulate learning behavior more consistently over time, thereby strengthening longterm study habits(Thiel & Hanssen, 2025). Within AI based learning environments, cognitive engagement becomes increasingly important because learners are required not only to access information but also to evaluate, interpret, and critically utilize AI generated outputs.

Overall, these findings indicate that study habits in the AI era are shaped through different psychological mechanisms. Emotion regulation mainly supports behavioral stability and learning persistence, whereas social skills encourage deeper cognitive engagement and more reflective AI based learning behavior. This pattern may also be associated with the characteristics of the respondents, most of whom belonged to Generation Z and reported frequent use of AI tools, particularly ChatGPT, in their daily academic activities. According to Prensky (2001) digital natives perspective, individuals who grow up in digital environments tend to prefer rapid information access and instant feedback. Consequently, although AI technologies support learning efficiency, they may simultaneously reduce opportunities for deeper cognitive processing if used passively. Therefore, strengthening social interaction, collaborative learning culture, and reflective AI literacy becomes essential to ensure that AI based study habits remain adaptive, critical, and academically meaningful.

CONCLUSION

This study aims to examine the role of emotion regulation, social skills, and cognitive engagement in shaping college students' study habits in the era of AI-based learning. The results show that emotion regulation and social skills have a significant direct effect on study habits, thus accepting hypotheses H1 and H3. Additionally, social skills are proven to have a significant effect on cognitive engagement (H5 accepted), and cognitive engagement has a significant effect on study habits (H6 accepted).

However, emotion regulation does not significantly affect cognitive engagement, thus rejecting hypothesis H4, and cognitive engagement does not mediate the relationship between emotion regulation and study habits (H6 rejected). Conversely, cognitive engagement is proven to partially mediate the relationship between social skills and study habits, thus accepting hypothesis H7. These findings indicate that social skills have a more complex and powerful mechanism of influence in shaping students' study habits, both directly and through increased cognitive engagement.

Conceptually, the results of this study confirm that the formation of study habits in the AI era does not only depend on emotional management skills, but is more influenced by social skills that encourage interaction, collaboration, and active cognitive engagement. In the context of AI-based learning, which tends to provide instant information, emotion regulation functions as a mechanism for stabilizing learning behavior, while social skills act as the main catalyst for cognitive engagement and deep learning.

From a practical standpoint, these findings have implications for education policymakers and governments. Efforts to improve the quality of learning in the AI era should not only focus on providing technology, but also on strengthening emotion regulation, social skills, and student engagement strategies. Governments and universities can design intervention programs, curricula, and support services that encourage academic collaboration, responsible AI literacy, and the formation of independent learning habits. With a more comprehensive policy approach, the learning process will be more adaptive, productive, and sustainable in the face of technological developments.

Although this study provides empirical contributions to understanding the role of emotion regulation, social skills, and cognitive engagement in students' study habits in the era of AI-based learning, several limitations need to be considered. The use of a cross-sectional design limits the drawing of causal conclusions, while self-report data collection has the potential to cause subjective bias among respondents. In addition, the limitation of the sample to students of the Faculty of Economics and Business at a nationally accredited university limits the generalizability of the findings. Therefore, future research is recommended to use a longitudinal or experimental design, involve cross-disciplinary and cross-institutional samples, and include additional variables such as AI literacy, intrinsic motivation, and self-regulated learning as mediators or moderators to enrich the understanding of the formation of study habits in an AI-based learning ecosystem.

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