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Growth Mindset and AI Generative Dependency among Students: The Role of Achievement Goal Orientations

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ABSTRACT

The increasing integration of generative artificial intelligence (GenAI) in education has raised concerns regarding students' potential dependency on these technologies. This study examines the relationships between growth mindset, achievement goal orientations, and generative AI dependency among secondary school students in Indonesia. A total of 191 students (junior high school = 180; senior high school = 11) were selected using purposive sampling based on prior experience using GenAI for academic purposes. Using a quantitative cross-sectional survey and Partial Least Squares–Structural Equation Modeling (PLS-SEM) with SmartPLS 4, generative AI dependency was operationalized as psychological dependency characterized by cognitive preoccupation, negative consequences, and withdrawal. The results indicate that growth mindset significantly predicts mastery goal orientation ($\beta = 0.304$, $p < 0.001$) and performance goal orientation ($\beta = 0.284$, $p < 0.001$), but does not directly predict generative AI dependency ($\beta = 0.055$, $p = 0.599$). In addition, mastery goal orientation ($\beta = -0.213$, $p = 0.115$) and performance goal orientation ($\beta = 0.110$, $p = 0.469$) do not significantly predict generative AI dependency. The structural model explains a limited proportion of variance in generative AI dependency ($R^2 = 0.032$). These findings suggest that motivational constructs such as growth mindset and achievement goal orientations are associated with students' learning orientations but are insufficient to explain dependency-related engagement with generative AI. The study highlights the need for future research to incorporate regulatory and epistemic factors to better understand students' dependency on GenAI in educational contexts.

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1. INTRODUCTION

The rapid diffusion of generative artificial intelligence (GenAI) tools, including large language models and multimodal assistants, is reshaping contemporary learning environments across educational levels. Prior research highlights GenAI's potential to support personalized learning, scaffolding, and real-time feedback, thereby enhancing motivation, self-regulation, and academic performance when used thoughtfully (Giannakos et al., 2024; Mittal et al., 2024; Strielkowski et al., 2024; Gervacio, 2024; Hajian et al., 2025; Pan & Li, 2025). At the same time, growing concerns have emerged regarding psychological and pedagogical risks, including reduced originality, erosion of critical thinking, motivational stagnation, and ethical issues when students outsource core cognitive processes to AI systems (Giannakos et al., 2024; Liu et al., 2025; Saúde et al., 2024). Systematic reviews and conceptual frameworks consistently warn that uncritical over-reliance on AI dialogue systems may undermine deep processing, analytical reasoning, and autonomous decision-making, underscoring the need to move beyond adoption-focused perspectives toward a more nuanced understanding of GenAI dependency as a psychological phenomenon in education (Dickey et al., 2023; Hyde et al., 2024; Zhai et al., 2024).

GenAI dependency is conceptualized in this study as a maladaptive pattern of AI use characterized by cognitive preoccupation, withdrawal-like discomfort when access is limited, and continued reliance despite perceived negative academic or cognitive consequences. This pattern differs from frequent but regulated AI use, which may remain strategic and critically reflective (Chamo et al., 2025; Gervacio, 2024). Dependency reflects compromised self-regulation and weakened epistemic control, whereby students increasingly delegate sense-making, evaluation of sources, and problem-solving processes to AI systems, potentially masking shallow understanding and fragile competence (Giannakos et al., 2024; Hyde et al., 2024). Related frameworks caution that sustained dependence on generative AI may hinder the development of core skills such as problem solving, algorithmic thinking, and independent judgment, even when short-term performance appears improved (Dickey et al., 2023; Y. Shi & Xu, 2025; Walczak & Cellary, 2023).

Within this context, growth mindset theory offers a motivational lens for understanding how students approach generative AI. Growth mindset reflects beliefs that intelligence and abilities can be developed through effort, effective strategies, and support, in contrast to fixed beliefs about ability (Dweck & Yeager, 2021). Extensions of this framework include domain-specific beliefs, such as a technological growth mindset regarding the malleability of technology-related skills (T. Chow & To, 2025). Prior studies suggest that generative AI can support growth-oriented beliefs by framing errors as learning opportunities and providing iterative feedback (Hajian et al., 2025; Zain & Habib, 2025), while students' pre-existing mindsets may shape whether AI is used as a learning partner or as a shortcut for surface-level task completion (Y. Shi & Xu, 2025; Zain & Habib, 2025). However, motivational beliefs alone may not directly translate into concrete technology-use behaviors, indicating the need to examine how growth mindset relates to patterns of GenAI engagement, including susceptibility to dependency, through intermediate motivational mechanisms.

Achievement goal theory provides a motivational framework for explaining how students' mindsets may translate into concrete learning behaviors when using generative AI. The theory distinguishes mastery goals, which emphasize learning, competence development, and understanding, from performance goals, which focus on demonstrating ability and managing evaluative outcomes (Dweck & Leggett, 1988; Dweck & Yeager, 2021). In AI-integrated learning environments, these goal orientations shape how students engage with GenAI, determining whether AI is used as a tool for elaboration, self-explanation, and feedback or as a shortcut for rapid task completion and impression management (Gervacio, 2024; Pan & Li, 2025). Because growth mindsets are consistently associated with mastery-oriented motivation, while less adaptive beliefs are linked to performance-focused goals (Pan & Li, 2025), achievement goal orientations are conceptually positioned in this study as potential mediators between growth mindset and generative AI dependency.

Despite the growing body of research on generative AI in education, existing studies have primarily focused on adoption, attitudes, and learning outcomes, with relatively limited empirical attention to psychological dependency on AI systems (Deroncele-Acosta et al., 2025; Giannakos et al., 2024; Mittal et al., 2024). Although prior work indicates that GenAI can support motivation, self-regulation, and well-being when embedded in thoughtful pedagogy, it provides little insight into when and why these tools become objects of maladaptive reliance (Gervacio, 2024; Pan & Li, 2025; Saúde et al., 2024). Research on technological growth mindset and GenAI usage demonstrates that mindset-related beliefs predict AI adoption and cognitive appraisals, yet rarely examines dependency-related outcomes or the role of achievement goal orientations (T. S. Chow & To, 2025). Similarly, conceptual and qualitative accounts of AI as a learning partner highlight adaptive engagement but do not empirically model dependency processes, particularly among secondary school learners (Chamo et al., 2025; Zain & Habib, 2025). Consequently, the motivational mechanisms linking students' beliefs and achievement goals to generative AI dependency remain empirically under-specified, and to date, no study has simultaneously examined growth mindset, achievement goal orientations, and generative AI dependency within a single explanatory framework in secondary school contexts (Liu et al., 2025; Zhai et al., 2024).

Secondary school students constitute a particularly important population for examining generative AI dependency. During early and middle adolescence, self-regulatory capacities, metacognitive skills, and academic identities are still developing, which may increase vulnerability to unregulated reliance on external cognitive supports such as generative AI tools. In addition, secondary students typically face strong assessment pressures and performance-based evaluations, while often possessing limited formal AI literacy and critical guidance on responsible AI use. School-level policies regarding AI use, along with restricted access to technology in classroom settings, may further shape how and why students turn to generative AI for academic tasks. Examining motivational predictors of generative AI dependency at this developmental stage is therefore crucial for understanding early patterns of AI reliance and for informing preventive educational interventions before such behaviors become entrenched.

The present study addresses these gaps by examining the relationships between students' growth mindset, achievement goal orientations, and generative AI dependency in a secondary school context. Specifically, the study tests whether growth mindset is associated with generative AI dependency, examines the roles of mastery and performance goal orientations in students' engagement with GenAI, and evaluates the potential mediating effects of achievement goal orientations in the relationship between growth mindset and dependency. Theoretically, this study contributes by clarifying the distinction between motivational beliefs (growth mindset and achievement goals) and dependency-related engagement with generative AI, integrating mindset and achievement goal theories within an empirical model of GenAI use. While the study is theoretically informed by perspectives on self-regulated learning and epistemic agency, these constructs are not directly measured and are therefore positioned as potential explanatory mechanisms for future research rather than as tested components of the present model. By focusing on secondary school students, the study provides contextually grounded insights into how motivational profiles relate to patterns of generative AI engagement during a critical developmental stage.

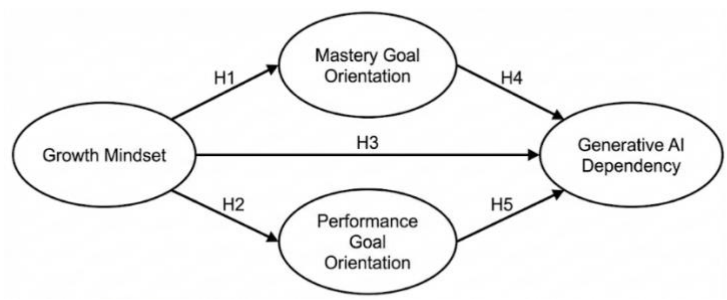

Figure 1. Research Framework

Based on growth mindset theory and achievement goal theory, the present study proposes a motivational framework linking students' beliefs about the malleability of abilities to their patterns of engagement with generative AI through achievement goal orientations. Growth mindset reflects students' beliefs that intelligence and personal attributes can be developed through effort and effective strategies. Prior research consistently shows that such beliefs are associated with more adaptive achievement-related motivations, particularly mastery-oriented goals, and in some contexts, performance-oriented goals.

Accordingly, this study hypothesizes that growth mindset is positively associated with both types of achievement goal orientation.

H1: Growth mindset is positively associated with mastery goal orientation.
H2: Growth mindset is positively associated with performance goal orientation.

From a motivational perspective, students who endorse a growth mindset may be less inclined to rely excessively on external cognitive supports, as they tend to value effortful learning and self-improvement. Therefore, growth mindset is expected to be negatively related to dependency on generative AI.

H3: Growth mindset is negatively associated with generative AI dependency.

Achievement goal theory further suggests that students' orientations toward mastery or performance shape how they engage with learning tools. Mastery-oriented students are expected to use generative AI in a regulated and reflective manner, whereas performance-oriented students may be more likely to rely on AI instrumentally to achieve desired outcomes with minimal effort. Thus, achievement goal orientations are hypothesized to be associated with generative AI dependency.

H4: Mastery goal orientation is negatively associated with generative AI dependency.
H5: Performance goal orientation is positively associated with generative AI dependency.

Finally, integrating growth mindset theory with achievement goal theory, this study proposes that achievement goal orientations may function as motivational mechanisms linking growth mindset to generative AI dependency. Specifically, growth mindset may influence dependency patterns indirectly through its effects on mastery and performance goal orientations.

H6: Mastery goal orientation mediates the relationship between growth mindset and generative AI dependency.
H7: Performance goal orientation mediates the relationship between growth mindset and generative AI dependency.

2. METHODS

2.1 Research Design

This study employed a quantitative cross-sectional survey design with an explanatory approach to examine the relationships between growth mindset, achievement goal orientation, and generative AI dependency in educational settings. Specifically, the proposed model tested the mediating roles of mastery and performance goal orientations in the relationship between growth mindset and students' dependency on generative artificial intelligence.

2.2 Participants

A total of 191 secondary school students participated in this study. The participants were drawn from junior high schools (SMP) and senior high schools (SMA), including both public and private educational institutions located in Purwokerto and Purbalingga, Indonesia. The majority of respondents were junior high school students (n = 180), while 11 students were enrolled in senior high school. Regarding gender distribution, 84 participants were male (43.98%) and 107 were female (56.02%).

In terms of age, most participants were 14 years old (43.46%), followed by those aged 15 years (24.61%) and 13 years (15.71%). Participants aged 12 years accounted for 6.81%, those aged 16 years for 7.33%, and only a small proportion were aged 17–18 years (2.09%). Overall, the age distribution represents early to middle adolescence, a developmental period that is particularly relevant for examining mindset formation, achievement-related motivation, and emerging patterns of AI generative tool use in learning contexts.

Participants were selected using purposive sampling, with the inclusion criterion that students had prior experience using generative AI tools (e.g., ChatGPT or similar applications) for academic purposes. The sample size met the minimum requirements for PLS-SEM analysis based on the 10-times rule, as the number of respondents exceeded ten times the maximum number of structural paths directed at any latent construct in the model.

2.3 *Measures*

Three validated instruments were used to measure growth mindset, achievement goal orientation, and generative AI dependency.

2.3.1 Growth Mindset

Growth mindset was measured using the Implicit Theory Measure developed by Dweck et al. (1995). In this study, the construct was operationalized through two domains: intelligence and moral character, reflecting students' beliefs about the malleability of cognitive ability and moral traits.

The instrument consisted of six items, including three items assessing intelligence beliefs and three items assessing moral beliefs, rated on a 6-point Likert scale ranging from 1 (strongly agree) to 6 (strongly disagree). All items were phrased as fixed mindset statements and therefore reverse-coded, such that higher scores indicated a stronger growth mindset, representing the belief that intelligence and moral character can be developed through effort, learning, and experience.

This scale has been used in prior research, including a study by Herdian, Qingrong, and Nuryana (2024), which reported satisfactory psychometric properties in educational contexts. In the present study, the growth mindset scale demonstrated good internal consistency, with a Cronbach's alpha coefficient of $\geqslant 0.70$.

2.3.2 Achievement Goal Orientation

Achievement goal orientations were measured using an instrument developed by Midgley et al. (1998, 2000) based on the Patterns of Adaptive Learning Scales (PALS). The instrument assesses two core dimensions: mastery goal orientation and performance goal orientation. The scale comprised 21 items, including 11 mastery-oriented items and 10 performance-oriented items, rated on a 4-point Likert scale ranging from 1 (strongly disagree) to 4 (strongly agree). Reliability analysis indicated that both dimensions demonstrated acceptable internal consistency, with Cronbach's alpha values exceeding 0.70. Higher mastery goal orientation scores reflect a stronger focus on learning, understanding, and competence development, whereas higher performance goal orientation scores indicate a greater emphasis on outperforming others and demonstrating relative ability.

2.3.3 Generative AI Dependency

Generative AI dependency was measured using the Generative AI Dependency Scale developed by Goh et al. (2025). This scale was specifically designed to capture psychological dependency on generative AI systems, distinguishing it from traditional technology addiction measures. The instrument consisted of 11 items across three dimensions: cognitive preoccupation, negative consequences, and withdrawal. Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The scale demonstrated excellent internal consistency, with reported Cronbach's alpha values ranging from 0.92 to 0.93. Higher scores indicate stronger psychological dependency on generative AI, characterized by persistent cognitive engagement, perceived negative academic consequences, and emotional discomfort when access to AI tools is restricted.

2.4 *Data Collection Procedure*

Data were collected in November 2025 using an online questionnaire administered to secondary school students in Indonesia. The survey was distributed through school communication channels with the assistance of teachers and school administrators. Prior to data collection, permission to conduct the study was obtained from the relevant educational institutions. Regarding access to generative AI, students primarily used GenAI tools through their own personal devices. At the time of data collection, generative AI use generally occurred outside formal classroom settings and was not part of regular classroom instruction, in line with prevailing school-level policies.

Before completing the questionnaire, all participants were provided with a clear explanation of the study objectives, the voluntary nature of participation, and the estimated time required to complete the survey. Students were informed that there were no right or wrong answers and were encouraged to respond honestly based on their own learning experiences with Generative AI. Informed consent was obtained electronically before respondents could proceed to the questionnaire. For underage participants, the data collection procedure followed school-approved ethical guidelines, and participation was conducted under teacher supervision.

The questionnaire was completed anonymously, and no personally identifiable information was collected. All responses were treated with strict confidentiality and were used solely for research purposes. Participants were informed that they could withdraw from the study at any time without any academic consequences. To minimize response bias, the survey was completed individually and did not affect students' grades or school evaluations.

The online data collection approach allowed for efficient access to students from different schools and grade levels, while ensuring flexibility and convenience for participants. After the data collection period ended, the responses were screened for completeness and response quality prior to data analysis.

2.5 Data Analysis

Data analysis was conducted using SmartPLS 4 (version 4.0.9.9) with the Partial Least Squares–Structural Equation Modeling (PLS-SEM) approach (Ringle et al., 2022). The analysis followed a stepwise procedure.

First, preliminary data screening was conducted to examine data completeness, identify response patterns indicating inattentive responding, and ensure consistent score direction through reverse coding of negatively worded items. Higher scores across all measures consistently represented higher levels of the respective constructs.

Second, the measurement model was evaluated by assessing indicator reliability using outer loadings, with values $\geq$ 0.70 considered ideal and values between 0.60 – 0.70 deemed acceptable if construct reliability and validity were maintained. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability, with values $\geq$ 0.70 indicating adequate reliability. Convergent validity was examined using the average variance extracted (AVE), with values $\geq$ 0.50 considered satisfactory. Discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT), applying a threshold of < 0.90.

Third, the structural model was assessed by examining multicollinearity among predictor constructs using the variance inflation factor (VIF), with values below 3.0 indicating no multicollinearity concerns. The significance of path coefficients was tested using a bootstrapping procedure with 5,000 resamples, applying a significance level of $p < 0.05$. Fourth, mediation effects of achievement goal orientations were tested using bootstrapped indirect effects. Mediation was classified as full or partial based on the significance of both direct and indirect paths.

2.6 Ethical Considerations

This study was conducted in accordance with ethical research principles. Participation was voluntary, informed consent was obtained, respondent anonymity was ensured, and all data were treated confidentially and used solely for academic purposes

3. FINDINGS AND DISCUSSION

The results are presented in three stages: measurement model evaluation, structural model evaluation, and mediation analysis

3.1 Measurement Model Evaluation

Table 1. Descriptive Statistics of Study Variables

Construct	Mean	SD
Growth Mindset	3.76	1.41
Mastery Goal Orientation	3.13	0.78
Performance Goal Orientation	2.79	0.88
Generative AI Dependency	2.52	1.10

Prior to measurement model evaluation, descriptive statistics were examined to describe the general characteristics of the study variables. As presented in Table 1, means and standard deviations are reported for all constructs. In addition, distributional properties were inspected using skewness and kurtosis values at the indicator level, with no indications of extreme departures from normality. Overall, the data were deemed suitable for subsequent PLS-SEM analysis. The measurement model was evaluated to assess indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All constructs in this study were specified as reflective.

Table 2. Reliability and Convergent Validity of the Measurement Model

Construct	Items	Loadings	Cronbach's α	Composite Reliability	AVE
Growth Mindset	INTELLIGENCE1	0.658	0.822	0.866	0.522
	INTELLIGENCE2	0.686			
	INTELLIGENCE3	0.606			
	MORAL1	0.796			
	MORAL2	0.783			
	MORAL3	0.784			
Mastery Goal Orientation	AGOM10	0.759	0.855	0.885	0.527
	AGOM11	0.774			
	AGOM2	0.714			
	AGOM4	0.868			
	AGOM7	0.805			
	AGOM8	0.591			
	AGOM9	0.747			
Performance Goal Orientation	AGOP1	0.804	0.852	0.892	0.627
	AGOP2	0.867			
	AGOP3	0.829			
	AGOP4	0.635			
	AGOP5	0.803			
Generative AI Dependency	NC2	0.588	0.854	0.887	0.535
	NC3	0.663			
	NC4	0.563			
	WD1	0.820			
	WD2	0.838			
	WD3	0.847			
	WD4	0.743			

As presented in Table 2, the measurement model demonstrated satisfactory reliability and convergent validity across all constructs. The standardized factor loadings ranged from 0.563 to 0.868, indicating that the indicators adequately represented their respective latent variables. Although several indicators exhibited loadings between 0.60 and 0.70, these items were retained because their inclusion did not adversely affect construct-level reliability or convergent validity.

Internal consistency reliability was supported, with Cronbach's alpha values ranging from 0.822 to 0.855 and composite reliability values ranging from 0.866 to 0.892, all exceeding the recommended threshold of 0.70. These results indicate that the measurement instruments demonstrated adequate to good internal consistency. Convergent validity was further confirmed, as all average variance extracted (AVE) values exceeded the minimum criterion of 0.50, suggesting that each construct accounted for more than half of the variance in its indicators. Overall, these findings indicate that the measurement model met the recommended psychometric criteria and was therefore suitable for subsequent structural model analysis.

Table 3. Discriminant Validity Assessment Using the Heterotrait–Monotrait Ratio (HTMT)

Constructs	AI Dependency	Growth Mindset	Mastery Goal Orientation	Performance Goal Orientation
AI Dependency	—			
Growth Mindset	0.135	—		
Mastery Goal Orientation	0.180	0.302	—	
Performance Goal Orientation	0.159	0.294	0.595	—

Discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT). As shown in Table 3, all HTMT values ranged from 0.135 to 0.595, which are substantially below the recommended threshold of 0.90. These results indicate that each construct in the model, growth mindset, mastery goal orientation, performance goal orientation, and generative AI dependency, is empirically distinct from the others. Therefore, the measurement model demonstrates adequate discriminant validity and is suitable for subsequent structural model analysis.

Overall, the measurement model demonstrated satisfactory indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All evaluation criteria were met, supporting the adequacy of the measurement model for subsequent structural model and mediation analyses.

3.2 Structural Model Evaluation

The structural model was evaluated to examine the hypothesized relationships among growth mindset, achievement goal orientations (mastery and performance), and generative AI dependency. The assessment followed established guidelines for partial least squares structural equation modeling (PLS-SEM), including collinearity diagnostics, path coefficient significance testing, and the coefficient of determination (Hair et al., 2019).

3.2.1 Collinearity Assessment

Prior to evaluating the structural relationships, collinearity among predictor constructs was assessed using the variance inflation factor (VIF). All inner VIF values ranged from 1.000 to 1.446, which are well below the recommended threshold of 3.0. These results indicate that multicollinearity is not a concern in the structural model and that the estimated path coefficients can be interpreted reliably.

Table 4. Collinearity Assessment (Inner VIF)

Endogenous Construct	Predictor Construct	VIF
AI Dependency	Growth Mindset	1.128
	Mastery Goal Orientation	1.446
	Performance Goal Orientation	1.428
Mastery Goal Orientation	Growth Mindset	1.000
Performance Goal Orientation	Growth Mindset	1.000

3.2.2 Path Coefficients

The hypothesized relationships were examined using a bootstrapping procedure with 5,000 resamples. Table X presents the standardized path coefficients (β), t-values, p-values, and 95% bootstrapped confidence intervals for all structural paths. Growth mindset significantly predicted mastery goal orientation (H1; $\beta = 0.304$, $p < 0.001$) and performance goal orientation (H2; $\beta = 0.284$, $p < 0.001$). However, growth mindset did not have a significant direct effect on generative AI dependency (H3; $\beta = 0.055$, $p = 0.599$). Similarly, mastery goal orientation (H4; $\beta = -0.213$, $p = 0.115$) and performance goal orientation (H5; $\beta = 0.110$, $p = 0.469$) did not significantly predict generative AI dependency. The bootstrapped confidence intervals for all non-significant paths included zero, further confirming the absence of statistically meaningful effects. In contrast, the confidence intervals for the paths from growth mindset to both achievement goal orientations did not include zero, supporting their robustness.

Table 5. Path Coefficients (Bootstrapping Results)

Hypothesis	Structural Path	β	t-value	p-value	Decision
H1	Growth Mindset → AI Dependency	0.055	0.525	0.599	Not supported
H2	Growth Mindset → Mastery GO	0.304	4.858	< 0.001	Supported
H3	Growth Mindset → Performance GO	0.284	3.943	< 0.001	Supported
H4	Mastery GO → AI Dependency	−0.213	1.575	0.115	Not supported
H5	Performance GO → AI Dependency	0.110	0.724	0.469	Not supported

3.2.3 Structural Model Overview

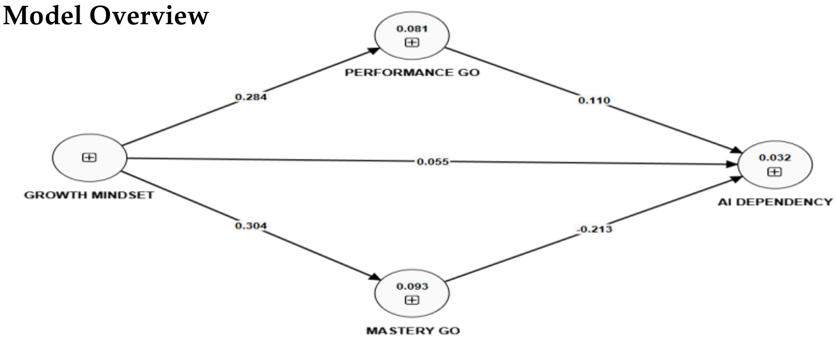

Figure 2. Final structural model showing standardized path coefficients (β)

The coefficient of determination (R^2) was used to assess the explanatory power of the structural model. The model explained 9.3% of the variance in mastery goal orientation ($R^2 = 0.093$) and 8.1% of the variance in performance goal orientation ($R^2 = 0.081$), indicating small to moderate explanatory power for motivational outcomes. In contrast, the model explained only 3.2% of the variance in generative AI dependency ($R^2 = 0.032$). This very low R^2 value suggests that the motivational constructs included in the model account for only a limited proportion of variance in dependency-related engagement with generative AI.

The structural model explains a very small proportion of variance in generative AI dependency ($R^2 = 0.032$). This indicates that the motivational constructs included in the model—growth mindset and achievement goal orientations—account for only limited variance in students' dependency-related engagement with generative AI. Rather than suggesting strong explanatory relationships, this finding implies that key predictors of generative AI dependency are likely omitted from the present model. Accordingly, the current results should be interpreted with caution and viewed as an initial step in examining motivational factors, while highlighting the need for future models to incorporate additional regulatory, epistemic, and contextual predictors to better explain dependency-related behaviors.

3.3 Mediation Analysis

Table 6. Mediation Analysis: Specific Indirect Effects

Indirect Path	β (Indirect Effect)	t-value	p-value	Mediation
Growth Mindset → Mastery Goal Orientation → AI Dependency	−0.065	1.389	0.165	Not supported
Growth Mindset → Performance Goal Orientation → AI Dependency	0.031	0.683	0.495	Not supported

The mediating roles of mastery goal orientation and performance goal orientation in the relationship between growth mindset and generative AI dependency were examined using a bootstrapping procedure. The results showed that the indirect effect of growth mindset on generative AI dependency through mastery goal orientation was not statistically significant ($\beta = -0.065$, $t = 1.389$, $p = 0.165$). Similarly, the indirect effect through performance goal orientation was also non-significant ($\beta = 0.031$, $t = 0.683$, $p = 0.495$). These findings indicate that achievement goal orientations do not mediate the relationship between growth mindset and generative AI dependency.

Discussion

Overall, the findings of this study show a clear pattern across the proposed hypotheses. Growth mindset significantly predicted mastery goal orientation (H1) and performance goal orientation (H2). However, growth mindset did not directly predict generative AI dependency (H3). In addition, neither mastery goal orientation (H4) nor performance goal orientation (H5) was significantly associated with generative AI dependency. Consequently, the mediation hypotheses involving achievement goal orientations (H6 and H7) were not supported. Taken together, these results indicate that motivational constructs such as growth mindset and achievement goal orientations are effective in explaining students' learning goals, but not their dependency-related engagement with generative AI. This distinction suggests that students' motivational orientations toward learning do not automatically translate into how they regulate or rely on AI tools in academic contexts.

Growth Mindset and Achievement Goals Orientation

The finding that growth mindset positively predicted both mastery and performance goal orientations (H1, H2) aligns with established theory and recent evidence. According to mindset theory, believing that abilities can grow (a growth mindset) encourages a focus on learning and improvement (Dweck & Yeager, 2021). Classic work by Dweck argues that students with a growth mindset adopt mastery (learning) goals, striving to develop competence, whereas a fixed mindset leads to performance goals aimed at validating one's ability (Dweck & Leggett, 1988). Our results confirm that growth-minded students indeed embrace mastery-oriented goals (H1), consistent with the idea that they value effort, challenges, and learning for its own sake. Indeed, respondents with a stronger growth mindset in our sample were more likely to endorse mastery-oriented goals, aligning with prior research linking incremental beliefs to a preference for challenging learning tasks (Mueller & Dweck, 1998).

Interestingly, growth mindset also showed a positive link to performance goal orientation (H2). This suggests that students who believe in malleable intelligence may still be motivated to outperform others or demonstrate competence, perhaps in a performance-approach sense (seeking achievement as proof of improvement). Recent research similarly found that growth mindset can foster both mastery and performance goals: for example, a study of high-achieving students reported that a growth mindset had significant positive paths to mastery, performance-approach, and even performance-avoidance goals (P. R. Wichaidit et al., 2025). Thus, having a growth mindset does not preclude setting competitive or normative goals; students may simultaneously aim to learn deeply and to excel relative to peers. Achievement goal theory Elliot & McGregor (2001) provides a framework for this, noting that individuals often pursue multiple goals (e.g. learning for mastery and outperforming for performance) in tandem.

In our context, the positive coefficients for both goal types indicate that growth-minded students are generally highly motivated: they tend to seek mastery and take on performance benchmarks. This dual-goal finding extends mindset theory by suggesting that believing in growth can energize various goal pursuits, not solely intrinsic learning goals. Overall, H1 and H2 reinforce the theoretical synergy between mindset and goals: endorsing a growth mindset appears to orient students towards challenging themselves (mastery) while also being open to achievement outcomes (performance).

Growth Mindset and AI Generative Dependency

Hypothesis 3 posited that growth mindset would directly reduce students' dependency on generative AI, but this was not supported – there was no significant relationship between the two. This null finding is notable because it suggests a conceptual disconnect between a student's motivational belief and their actual behavior with technology. Growth mindset did not directly predict students' generative AI dependency. This underscores an important distinction between motivational beliefs and technology use habits. Growth mindset influences why a student learns (their reasons and reactions to failure), but it does not directly control whether they become dependent on an AI tool. This aligns with research on related technology behaviors: for example, Lai et al. (2022) found that a growth mindset's positive effects on mental health operated indirectly through reduced problematic smartphone use.

One might expect, then, that growth-minded students would rely less on AI (seeking to solve problems themselves) or perhaps use AI more constructively. However, our data indicate that simply holding a growth mindset does not translate into any clear tendency to use or avoid generative AI tools. There are several possible explanations. First, using AI may be driven more by situational convenience or necessity (e.g. tight deadlines, difficult tasks) than by one's general belief about intelligence. A student can believe in self-improvement, yet still turn to ChatGPT for help if they are pressed for time or unsure about an assignment. In other words, motivational beliefs (like growth mindset) operate at the level of why a student learns, whereas AI dependency is a question of how they complete academic work. These operate on different planes – a student's philosophy of learning might not govern their day-to-day tool usage, especially if that usage is seen as a pragmatic shortcut. Second, it's possible that growth mindset influences learning strategies more than tool preference. Prior research has found that having a growth mindset encourages help-seeking and persistence (T. S. Chow & To, 2025), but whether that means using AI as a "helper" or deliberately avoiding AI to learn by oneself could vary. Our finding of no direct effect aligns with the idea that growth mindset alone is not a decisive factor in AI reliance. Notably, a recent study by Dinh (2024) reported that implicit self-theories (mindsets) did influence attitudes toward using ChatGPT

In other words, mindset may lead a student to use digital tools more judiciously, but it is the pattern of use (e.g. smartphone habits) that actually impacts outcomes. Similarly, our findings suggest that generative AI dependency is less about intelligence beliefs and more about self-regulation and context. Indeed, technology dependence has been conceptualized as a habit-formed psychological reliance. Other studies have linked heavy AI/chatbot use to factors like depression and anxiety (X. Zhang et al., 2025) have identified self-control as a key predictor of general Internet or smartphone addiction (Chen & Zhang, 2024). In summary, H3's lack of support underscores that a student's belief in growth does not straightforwardly dictate their reliance on generative AI. This highlights the conceptual gap between motivational beliefs and behavioral tech usage, indicating that other factors likely intervene in whether students become dependent on AI.

Achievement Goals and AI Dependency

The finding that achievement goal orientation, both mastery and performance, does not exert a significant effect on generative AI dependency suggests that achievement motivation alone is insufficient to explain patterns of engagement with this technology. Within the framework of Achievement Goal Theory, mastery goals emphasize the development of competence and deep understanding, whereas performance goals prioritize social comparison and demonstrable outcomes. However, in a learning environment characterized by "on-demand" technological support, the decision to rely on generative AI appears to be mediated more by how students regulate their learning processes and construe the role of AI in their cognitive activities than by their general goal orientations (Fan et al., 2024; Li et al., 2025; Mahniza et al., 2024; Xu et al., 2025). Recent studies indicate that while the use of generative AI may enhance short-term performance, it can simultaneously encourage cognitive offloading and metacognitive laziness, leading students to delegate thinking processes to the system without engaging in deep processing (Fan et al., 2024; Li et al., 2025). This dynamic is more closely related to epistemic control namely, the extent to which students feel the need to verify, critique, and understand AI-generated outputs—than to whether they are oriented toward mastery or performance goals (Li et al., 2025; Vadaparty et al., 2025; L. Zhang & Xu, 2024).

From a self-regulated learning (SRL) perspective, dependency on generative AI emerges when planning, monitoring, and self-evaluation are weak, resulting in the use of AI primarily as a substitute for cognitive effort rather than as a tool to structure and reflect upon learning (Iqbal et al., 2025; J. Shi et al., 2025; Xu et al., 2025). Empirical evidence shows that when metacognitive support and instructional design are intentionally aligned to strengthen SRL—such as through scaffolding, reflective feedback, and task designs that require critical dialogue with AI outputs—students are more likely to demonstrate epistemic agency by reading, testing, and critically evaluating generative AI responses instead of accepting them passively (Chang et al., 2023; Li et al., 2025; Vadaparty et al., 2025; Xu et al., 2025). Conversely, in the absence of adequate AI literacy and a robust self-regulatory framework, students across different goal orientations tend to exhibit similar usage patterns, relying on AI to complete tasks quickly at the expense of learning autonomy and independence (Dai et al., 2025; Fan et al., 2024; J. Shi et al., 2025; Wei, 2023; L. Zhang & Xu, 2024). Accordingly, generative AI dependency is more appropriately conceptualized as a phenomenon rooted in the quality of self-regulated learning, epistemic control, and AI literacy and competence, rather than as a direct derivative of the strength of students' achievement motivation.

Mediation Analysis: The Role of Achievement Goal Orientation

With regard to the mediation hypotheses, this study tested whether mastery goal orientation (H6) and performance goal orientation (H7) mediate the relationship between growth mindset and generative AI dependency. The results indicate that neither mastery goal orientation nor performance goal orientation significantly mediates this relationship. Accordingly, both mediation hypotheses (H6 and H7) were not supported. The finding that neither mastery nor performance goal orientation mediates the relationship between growth mindset and generative AI dependency should be interpreted from both conceptual and statistical perspectives. In structural equation modeling (SEM), mediation requires a significant path from the predictor to the mediator and from the mediator to the outcome, as well as an indirect effect that differs significantly from zero, typically tested through the product-of-coefficients approach or bootstrapping procedures (Sarstedt & Moisescu, 2023). In the domain of academic achievement, growth mindset is consistently shown to be strongly associated with mastery goals, which in turn mediate academic outcomes such as grade point average (GPA) (P. Wichaidit et al., 2025). However, in the context of technology use particularly dependency on generative AI the direct relationship between achievement goal orientation and technology-related behavior appears weak and inconsistent. Prior research on goal orientation and technology use indicates that mastery goals are more closely linked to focused, on-task learning engagement rather than to indiscriminate increases in digital tool usage (Rivers, 2021). Consequently, the causal and statistical conditions for mediation are not satisfied, as one or both paths (growth mindset → goal orientation; goal orientation → AI dependency) lack sufficient strength at the level of dependency-related behavior.

From a theoretical standpoint, these findings underscore a fundamental distinction between motivational constructs (e.g., achievement goal orientation) and technology dependency behaviors. Achievement goal orientation reflects learning intentions (mastery versus outperforming others) and is more commonly associated with learning strategies, self-efficacy, and academic emotions (Frumos et al., 2024; Honicke et al., 2020; Rivers, 2021). In contrast, dependency on AI is primarily related to patterns of cognitive and metacognitive regulation that are partially transferred to technology, including metacognitive laziness, cognitive offloading, and reduced epistemic vigilance (Fan et al., 2024; Iqbal et al., 2025; Yan et al., 2025). Recent research on generative AI suggests that the key mechanisms linking AI use to learning outcomes involve self-regulated learning strategies, self-efficacy and engagement, shared metacognition, and cognitive offloading, rather than goal orientation (Fan et al., 2024; Iqbal et al., 2025; Liang et al., 2023; Molenaar et al., 2022; Rivers, 2021). Accordingly, the relationship between growth mindset and generative AI use or dependency is more likely to be mediated by constructs such as performance or effort expectancy and technology anxiety (T. Chow & To, 2025), epistemic beliefs about AI-generated knowledge, as well as AI literacy and metacognitive control, which shape how individuals evaluate, verify, and regulate their reliance on AI (Molenaar et al., 2022; Yan et al., 2025). Taken together, these findings suggest that achievement goal orientation does not constitute the primary psychological mechanism linking growth mindset to generative AI dependency; instead, future mediation models should focus on learning regulation variables and epistemic beliefs that more directly govern the extent to which cognitive and metacognitive functions are delegated to AI. These findings reinforce the view that achievement goal orientation does not constitute the primary psychological mechanism linking growth mindset to generative AI dependency.

Theoretical and Conceptual Implications

This study contributes to growth mindset theory by reaffirming that growth mindset functions as a foundational motivational belief that shapes students' achievement goal orientations. Consistent with mindset theory, students who endorse a malleable view of intelligence are more likely to adopt both mastery and performance goal orientations, indicating that growth mindset remains a robust antecedent of goal-related motivational processes in contemporary learning contexts. At the same time, the findings extend achievement goal theory by demonstrating that while growth mindset effectively explains why students orient themselves toward certain learning goals, these goal orientations do not necessarily translate into technology-related dependency behaviors. This suggests that achievement goals primarily operate at the level of learning motivation and goal pursuit, rather than directly governing how students engage with or rely on emerging learning technologies such as generative AI.

More importantly, this study advances the literature on generative AI use in education by highlighting a conceptual boundary between motivational constructs and AI dependency. The absence of significant effects from growth mindset and achievement goal orientations on generative AI dependency indicates that dependency on AI tools cannot be sufficiently explained by motivational beliefs alone. Conceptually, these findings position generative AI dependency as a phenomenon more closely aligned with self-regulation, epistemic agency, and digital and AI literacy. Rather than reflecting what students aim to achieve (goals) or how they view their abilities (mindset), AI dependency appears to be shaped by how students regulate their learning processes, exercise critical control over knowledge generated by AI, and possess the competencies required to use AI tools responsibly and reflectively. Thus, this study underscores the need for future theoretical models of AI use in education to move beyond motivation-centered frameworks and more explicitly incorporate regulatory and epistemic dimensions of human–AI interaction

4 CONCLUSION

This study examined the relationships between growth mindset, achievement goal orientations, and generative AI dependency among secondary school students. The findings indicate that growth mindset significantly predicts both mastery and performance goal orientations, confirming its role in shaping students' motivational orientations toward learning. However, neither growth mindset nor achievement goal orientations were found to significantly predict generative AI dependency. Taken together, the results suggest that motivational variables alone are insufficient to explain dependency-related engagement with generative AI. While growth mindset and achievement goal orientations are meaningfully associated with students' learning goals, they do not adequately account for students' reliance on generative AI tools. This distinction highlights the need to differentiate between motivational beliefs and technology-related dependency behaviors in educational research. Accordingly, future studies should extend the present model by explicitly examining regulatory and epistemic factors, such as self-regulated learning and epistemic agency, as potential mediators or moderators of generative AI dependency. By maintaining a clear separation between empirically tested findings and theoretical implications, this study provides a cautious and evidence-based foundation for subsequent research on generative AI use in secondary education.

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