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How generative artificial intelligence tools support self-directed learning: Implications for students' learning motivation and design thinking

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Abstract

Generative artificial intelligence (GenAI) tools have introduced promising opportunities for enhancing learning and automated assessment. Self-directed learning (SDL) and a design thinking mindset (DTM) have also been recognized as promising pedagogical approaches that support and contribute to advancing the Sustainable Development Goals. Although prior research has suggested that components of SDL may influence motivation and that motivation may be associated with DTM ability, there remains a noticeable gap in empirical studies examining the interrelationships among these variables. Grounded in the principles of SDL, the present study investigates the use of GenAI tools in assessing students' DTM. A quantitative study was conducted with a sample of 379 university students, and the data collected through validated measurement instruments were analyzed using structural equation modeling to test and verify the proposed structural model. Empirical findings revealed that the use of GenAI tools for assessment significantly influenced all components of SDL, ultimately leading to enhanced learning motivation. Furthermore, awareness, learning strategies, learning activities, and interpersonal skills were found to mediate the relationship between the use of GenAI tools in assessment and students' learning motivation. Interestingly, students' self-assessment did not significantly affect learning motivation and did not play a mediating role between GenAI tools-based assessment and motivation. A particularly noteworthy finding is the absence of a significant relationship between motivation and DTM. This study highlights the role of GenAI tools in relation to students' learning motivation and the development of their DTM, offering important implications for policies governing virtual learning environments and for instructional practices.

Keywords: generative AI tools, self-directed learning, learning motivation, design thinking mindset, higher education students, structural equation modeling



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Introduction

The proliferation of Generative artificial intelligence (GenAI) tools has generated diverse perspectives among faculty and students in higher education (Kutty et al., 2024). These tools substantially improve students' access to immediate evaluations and prompt answers related to assessing design-based outputs. GenAI tools have rapidly become transformative educational technologies, demonstrating strong capabilities in automated assessment, idea generation, communication, and data analysis (Samala et al., 2025). They further support personalized learning through knowledge extraction and incremental adaptation. However, despite enhancing feedback interaction and learning support, GenAI tools also raise significant ethical concerns, including accountability, data privacy, plagiarism, and algorithmic opacity (Zhan et al., 2025). Therefore, higher education (HE) institutions must address these risks while ensuring responsible use and safeguarding academic integrity. Nevertheless, growing scholarly attention has also emphasized the educational potential of GenAI tools when implemented within appropriate pedagogical and ethical frameworks.

In this context, GenAI tools increasingly function as responsive learning partners that adapt dynamically to learner-initiated interactions. They generate outputs based on prompt patterns rather than predefined rules, enabling flexible, multi-pathway responses (Wang et al., 2024). This adaptability supports highly personalized learning, adaptive feedback, and innovative assessment practices (Strielkowski et al., 2024). Empirical evidence further demonstrates the positive impact of GenAI tools on self-regulation strategies and task attitudes (Aladini et al., 2024). Recent research has increasingly examined the educational value of GenAI tools. Bin-Nashwan et al. (2023) highlighted their role in shaping academic competence and self-esteem. Von Garrel and Mayer (2023) confirmed the effectiveness of GenAI tools in resolving comprehension difficulties and supporting conceptual understanding. Gao et al. (2024) further demonstrated positive effects on students' motivation, learning strategies, and academic performance.

On the other hand, several systematic reviews have been conducted to further explore how current generations interact with GenAI tools (Alakabawy, 2024; Tlili et al., 2025). However, a gap remains regarding the impact of using GenAI tools in automated assessment on students' self-directed learning (SDL) components and their motivation. Moreover, the literature still lacks sufficient evidence on the use of GenAI tools in learning concerning how students' learning motivation (LM) affects learning outcomes, particularly in enhancing students' design thinking mindset (DTM). Little is known about how the use of GenAI tools in assessment is associated with DTM. The present study addresses these gaps by identifying students' SDL components as a catalyst for motivating learning and, consequently, strengthening their DTM. It is important to note that research exploring the enhancement of DTM through GenAI tools remains scarce. Bai and Wang (2025) indicated

that future research should investigate the impact of GenAI tools on students' cognitive dimensions (e.g., DTM). Importantly, this study is intended to inform key decision-makers in higher education settings, including instructors, curriculum designers, and institutional policymakers responsible for the design, implementation, and evaluation of GenAI-supported assessment practices. Clarifying this intended audience strengthens the practical orientation of the study and its relevance for evidence-based decision-making in educational settings. Using SDL as the theoretical framework, this study addresses these gaps through four objectives:

- Investigate the impact of using GenAI tools in assessment on students' SDL (i.e., awareness, learning strategies, learning activities, assessment, and interpersonal skills);
- Investigate the impact of students' SDL (i.e., awareness, learning strategies, learning activities, assessment, and interpersonal skills) on students' LM;
- Explore the impact of students' LM on improving their DTM; and
- Study the mediating role of students' SDL (i.e., awareness, learning strategies, learning activities, assessment, and interpersonal skills) in enhancing students' DTM.

By leveraging SDL, the study contributes to the literature by examining the components of SDL (awareness, learning strategies (LS), learning activities (LA), evaluation, and interpersonal skills (IS) in explaining students' motivation to learn and improving their DTM. It also examines Components of SDL as mediators between the use of GenAI tools in assessment and students' LM, which, to our knowledge, have not been studied before. In addition, to better position the novelty of the study relative to closely related recent work, this research extends the emerging literature by examining a unified structural model that integrates GenAI tool use, SDL components, learning motivation, and DTM. This integrated perspective further differentiates the present study from closely aligned contributions and strengthens its theoretical and empirical positioning within the evolving GenAI-in-education literature (Anders & Speltz, 2025; Chugh et al., 2025).

Theoretical background and hypotheses development

Self-directed learning

SDL is “learning in which decisions about what to learn, how to learn it, and how to determine whether one has learned something well enough are all in the hands of the learners” (James, 1987, p.3). SDL is a basic need for students to interact with GenAI tools. Students who have the opportunity to learn with GenAI tools must take responsibility for planning, monitoring, and evaluating their own learning processes. Given the nature of GenAI tools, which rely on learner-centered learning, students' mastery of SDL components is considered a factor that increases the efficiency of learning processes. Studies show that students who are self-directed in learning with GenAI tools are more

successful (Owan et al. 2025). SDL, which is also closely linked to students' motivation, represents a key construct in learning with GenAI tools. SDL centers on the notions of motivation and satisfaction. SDL is linked to intrinsic and extrinsic motivation through its theoretical structure, and cannot be considered separate from the state of students' motivation (Hua et al., 2024). SDL identifies five essential components - awareness, LS, LA, evaluation, and IS that are necessary for optimal performance and intrinsic motivation (Williamson, 2007). Self-awareness constitutes a foundational component of SDL, reflecting students' understanding of the factors that enable autonomous regulation of their learning. Complementing this, LS refer to the methods learners employ to cultivate self-direction (Van Tonder et al., 2022). LA further represents the actions students must undertake to develop SDL, including the effective use of GenAI tools. Evaluation plays a critical role by enabling students to monitor their progress, identify areas for improvement and enhance self-efficacy through peer comparison (Wang et al., 2024). Additionally, IS are essential for learners to navigate social contexts and fully develop SDL capacities. Collectively, these SDL components contribute significantly to strengthening student motivation, improving learning outcomes, and supporting psychological well-being.

In this regard, it can be said that the elements of SDL are important for students' motivation levels and within their learning processes. Students who organize their own learning processes are actively involved in learning processes during and after the actual learning process. Wang et al. (2025) indicate that students should be self-directed for a successful learning experience through GenAI tools. Students who are able to SDL in learning processes with GenAI tools may achieve richer learning outcomes. The flexible, learner-centered and autonomous nature of GenAI tools requires increased use of SDL components (Li et al. 2025). On the other hand, SDL has long been researched as an approach that motivates students to take responsibility and control over cognitive (self-monitoring) and contextual (self-management) processes in building and achieving purposeful learning outcomes (Dahal & Bhat, 2024). Motivation can be divided into entry motivation, which directs the student to the required task and task motivation, which refers to the motive that keeps the student engaged and persistent in the SDL process (Vu et al. 2022). These elements are interconnected and interactive. This study adopts Williamson's (2007) framework for understanding SDL in generative AI-assisted assessment.

GenAI tools and design create new trends and opportunities, including developments in personalized learning experiences, assessment methods, and accessibility. In addition, it generates ideas and summaries and provides new ideas for designers (Bin-Nashwan et al. 2023). GenAI tools increase the transparency and clarity of decisions, which promotes collaboration. One of the notable applications of GenAI tools is the integration of data from multiple sources into design assessments, which improves immersive design solutions (Chan, 2023), helping students understand their strengths and areas for improvement, and

thus enhancing DTM. On the other hand, the use of GenAI tools in SDL is a rapidly emerging research area; as a result, empirical studies in this field are rare (Jin et al. 2025). Among the available empirical evidence, Lin (2023) investigated the use of ChatGPT as a virtual tutor to facilitate SDL among adult learners in asynchronous internet contexts. However, challenges such as resource inaccuracy and over-reliance on GenAI tools are clearly evident, which may lead to a lack of DTM. In this context, the qualitative study by Mogavi et al. (2024) showed two different viewpoints. Some users viewed GenAI tools as transformative tools capable of enhancing students' self-efficacy and LM. Conversely, some users expressed concern about the potential for over-reliance on GenAI tools, claiming that it encourages superficial learning habits and weakens DTM. This divergence of opinions highlights the complexity of human-to- GenAI tools interaction in educational contexts, but it may also provide shortcuts for users to bypass some cognitive processes that may be important for SDL. Therefore, although GenAI tools are able to adapt to different learning styles, needs, approaches and goals. Anders and Speltz (2025) point to the importance of maintaining a high level of cognitive engagement and SDL so that students take responsibility for evaluating and reflecting on their own designs. Overall, this research shows that more comprehensive research is needed to discover how students use GenAI tools in the assessment process to understand their effects on SDL components. Given the widespread application of the SDL approach in educational research and its relevance to the current study, it was chosen as the basic framework. It will be used to investigate how the use of GenAI tools in assessments is related to the efficiency of SDL learning, and how these factors affect students' motivation to learn and their DTM.

Using GenAI tools in assessment and student awareness

The impact of GenAI tools on student learning is significant. GenAI tools stimulate thinking processes and activate prior experiences, which contribute to increasing students' awareness (Samala et al., 2025). GenAI tools can provide rich learning experiences that allow students to identify their own learning needs and weaknesses, set personal goals, and determine how to demonstrate their knowledge (Kim et al. 2025). Furthermore, assessments based on GenAI tools can provide immediate and adaptive feedback tailored to students' specific learning objectives (Strielkowski et al. 2024), enabling students to understand their personal strengths with group dynamics, thereby enhancing their awareness. It is expected that GenAI tools will be associated with higher levels of students' perceptions of consciousness in their learning experiences by understanding the factors that contribute to their self-direction. Therefore, it is assumed that:

H1: The use of GenAI tools in assessment has a positive impact on student awareness.

Using GenAI tools in assessment and student LS

GenAI tools provide personalized educational assistance and learning resources for students through intelligent recommendation systems. It can also simulate complex situations and help students with practical processes and problem-solving (Yao, 2024). In addition, GenAI tools can perform intelligent assessments, providing students with an analysis of their progress and learning effectiveness, thereby increasing their participation in group discussions using effective conversational methods (Yang, 2025). The tools will recommend specific methods and approaches for interacting with them. Therefore, this process requires stimulating self-LS, such as reasoning processes like evaluating the reliability and accuracy of information, along with knowledge of problem-solving approaches and solutions, and mapping concepts and contexts. Therefore, it is assumed that:

H2: The use of GenAI tools in assessment has a positive impact on students' LS.

Using GenAI tools in assessment and student LA

GenAI tools support LA, which students should engage in more actively and effectively. GenAI tools allow individuals time to focus on more creative tasks and explore more challenging topics. GenAI tools use a sophisticated conversational approach to answer, ask relevant questions and analyze ideas. In this context, the study by Youssef et al. (2024) concluded that GenAI tools are useful in providing resources and suggestions throughout the students' learning process, thereby increasing engagement and ambition in academic tasks. Therefore, GenAI tools may be associated with self-direction through diverse activities and methods linked to students' motivation to acquire knowledge, curiosity, and initiative (Li et al., 2025). Therefore, it is hypothesized that:

H3: The use of GenAI tools in assessment has a positive impact on student LA.

Using GenAI tools in assessment and student self-evaluation

GenAI tools provide unlimited interactive feedback through student-led formative dialogues for deep learning. Evaluation supported by GenAI tools enhances students' understanding of the importance of academic integrity, strengthens their research skills, and helps them understand complex issues (Ateeq et al. 2024). GenAI tools can support adaptive assessments, providing personalized and accurate evaluations of students' knowledge and skills (Vashishth et al. 2024). It was also found that students did not rely on the outputs of GenAI tools, but rather evaluated and critiqued them in terms of their accuracy and depth, a process that enhances their SDL components. Therefore, it is assumed that:

H4: The use of GenAI tools in assessment has a positive impact on student evaluation.

Using GenAI tools in assessment and IS

GenAI tools provide valuable opportunities to enhance IS by stimulating students' thinking processes and encouraging them to adopt critical perspectives on problems. In addition, GenAI tools can enhance student communication and facilitate collaborative work (Mıhçı Türker & Öztürk, 2024). GenAI tools are associated with an environment in which students may be encouraged to negotiate, participate, and make decisions in discussions. Yan et al. (2024) also highlighted that collaboration between students and GenAI tools enhances cognitive learning skills and improves communication effectively. Therefore, GenAI tools can facilitate personalized and collaborative learning experiences, which are known to enhance students' IS, enabling them to become self-directed learners. It is assumed that:

H5: The use of GenAI tools in assessment has a positive impact on students' IS.

Students' awareness and motivation to learn.

Students' awareness has a positive impact on their motivation to learn, and it supports SDL, which assumes that awareness is a crucial factor in promoting motivation (Kõiv & Saks, 2023). Kim's (2018) study provides further evidence supporting the relationship between students' awareness of factors that contribute to their self-direction, motivation, and learner outcomes. When students are able to maintain self-motivation, identify their own learning needs and weaknesses, update learning resources, their awareness is likely to increase, leading to increased motivation (Yang et al. 2025). It is assumed that:

H6: Student awareness has a positive impact on student motivation to learn.

Students' LS and their LM

LS, according to Pérez-Navío et al. (2023), are a set of organized actions taken by the student to achieve the learning goal efficiently in a socio-educational context. The use of SDL strategies depends, to a large extent, on the student's awareness, and also on other personal factors such as motivation to learn. Numerous studies have shown an important positive relationship between LS and motivation (Kikas et al. 2024). When students see themselves able to participate in discussions, role-playing, problem-solving, they are more likely to become self-directed in their learning process, which in turn enhances their motivation to engage in more academic activities. Based on these results, the following hypothesis was proposed:

H7: LS have a positive impact on students' motivation to learn.

Student LA and their LM

Providing a more stimulating and engaging learning environment depends on the LA available to students. The study by Bon et al. (2022) showed a positive relationship between

LA that supports curiosity and proactivity and increased levels of motivation. In the same context, it was found that using LA that relies on dialogue, idea analysis, and reflection increases motivation to learn (Wang et al. 2025). On the other hand, when students are given the opportunity to participate an LA that highlights important points and empathy, students' motivation to learn increases. Based on these results, the following hypothesis was proposed:

H8: LA have a positive impact on students' motivation to learn.

Student assessment and LM

Research has shown that when students realize there is a way to monitor their LA and progress, they become more motivated to engage in self-learning. For example, Zhu and Doo (2022) found a relationship between motivation, self-monitoring, self-management, and learners' use of MOOC courses for LS. Chuang et al. (2022) also highlighted that the key factor that greatly enhances self-motivation is the presence of activities that allow learning from failure and activities that allow the development of self-competencies. Research indicates that students who have a strong sense of peer evaluation and discover new learning challenges are more motivated to learn (Keller et al. 2025). These results indicate that student assessment in SDL can lead to higher levels of motivation for student learning. Therefore, it is assumed that:

H9: Student assessment has a positive impact on student motivation to learn.

IS and LM

The results of the study by Indrawati et al. (2023) showed that IS and constructive knowledge have a significant positive impact on motivation to learn. Therefore, HE institutions that focus on readiness for learning need to pay attention to IS, as these are of paramount importance in motivating students.. Furthermore, the study by Zamiri and Esmaeili (2024) indicates that if we want to improve students' motivation to learn, we must enhance there is, such as monitoring and adapting, negotiating and making decisions, and communicating. These results suggest that IS can lead to higher levels of motivation for students to learn. Therefore, it is assumed that:

H10: IS have a positive impact on students' motivation to learn.

Student LM and promoting DTM

DTM can be more rigorously understood when situated within foundational theories of design cognition and reflective practice. DTM can be more rigorously understood within foundational theories of design cognition and reflective practice. Cross conceptualizes design thinking as a distinct cognitive mode characterized by problem framing, abductive reasoning, and iterative refinement rather than linear analytical processes (Cross, 2011).

From this perspective, design thinking represents a way of reasoning under uncertainty rather than a set of procedural skills (Groeger & Schweitzer, 2020). Similarly, Schön (1983) highlights “reflection-in-action” as a continuous cycle of action and reflection, positioning DTM as an adaptive and metacognitive orientation shaped by ongoing reinterpretation of design problems (Dorst, 2019). Extending this view, Dorst emphasizes “design framing” as the ability to construct and reframe problem situations, reinforcing cognitive flexibility and tolerance for ambiguity as core elements of DTM (Dorst, 2015; Cross, 2011). The most common definition in education is that proposed by Razzouk and Shute (2012): an analytical and creative process that engages the individual in opportunities to experiment, create prototypes, gather feedback, and redesign. When students engage in DTM, they have to follow its steps to move forward with their designs, which increases their ability to perform better. DTM also refers to addressing problems in realistic situations, which may increase their motivation (Bender-Salazar, 2023). On the other hand, design thinking provides continuous opportunities to experiment with complex phenomena and think about ideas that can lead to high levels of student motivation. In other words, DTM promotes collaboration, iteration, and optimism, allowing participants to feel comfortable with ambiguity and failure in the problem-solving and improvement process (Schlott, 2024). Accordingly, the natural inclination towards DTM acts as an internal motivator. This intrinsic motivation is linked to the use of problem-solving and decision-making skills, which are part of DTM. This is because motivated students are more determined to fulfill commitments (Avsec & Jagiełło-Kowalczyk, 2021). Liu et al. (2023) highlighted that students who show greater motivation often possess advanced DTM. Therefore, it is assumed that:

H11: Students' LM has a positive impact on enhancing their DTM.

Mediation effect on students' awareness, LS, LA, evaluation, and IS.

SDL is defined as a process in which individuals, with or without the help of others, initiate the diagnosis of their educational needs, formulate learning objectives, identify the human and material resources necessary for learning, select and implement appropriate LS, and evaluate learning outcomes (Knowles, 1977). According to SDL theory, meeting these needs is crucial for enhancing motivation (Garrison, 1997). GenAI tools have the potential to provide personalized and adaptive learning experiences that enhance student awareness, thus mediating the relationship between the use of GenAI tools in assessments and LM. Furthermore, students who have high levels of SDL strategies tend to have strong confidence in their academic abilities (Rahman et al. 2025). When students interact with GenAI tools, they are more likely to see that these tools enhance their academic performance. GenAI tools provide opportunities to participate in group discussions using effective dialogue methods, active learning and problem-solving, which promote SDL

strategies, leading to greater mediation in this relationship. The results of the study by Sukkamart et al. (2023) indicate that SDL promotes intrinsic motivation, especially when the importance of the student-teacher relationship is emphasized. In addition, SDL and assessment activities play a vital role in maintaining motivation and engagement in educational environments. The collaborative and interactive features of GenAI tools can facilitate peer learning and social engagement, enhancing students' IS (Kovari, 2025) and thus mediating the relationship between the use of GenAI tools in assessments and LM. By leveraging GenAI tools to create personalized and adaptive assessments, educators can enhance students' intrinsic motivation, thereby supporting deeper engagement and more effective SDL outcomes. It is assumed that:

H11a: Awareness mediates the relationship between the use of GenAI tools in assessment and students' LM.

H11b: LS mediate the relationship between the use of GenAI tools in assessment and students' LM.

H11c: LA mediate the relationship between the use of GenAI tools in assessment and students' LM.

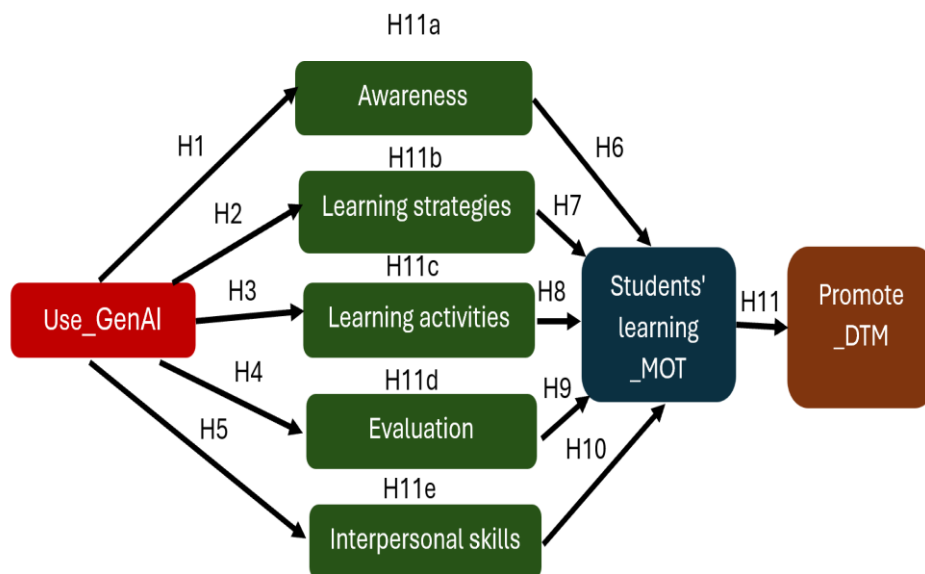
H11d: Evaluation mediates the relationship between the use of GenAI tools in assessment and students' LM.

H11e: IS mediate the relationship between the use of GenAI tools in assessment and students' LM.

Figure 1 shows the conceptual model of the current study.

Figure 1

Conceptual framework



Materials and methods

Research design

The research relied on the quantitative method. The research used the least squares partial structural equation model (SEM) as a basic analytical method. The least squares partial SEM was chosen because of its suitability for the complex research model involving multiple structures with mediating effects (Sarstedt & Ringle, 2021). This is important for this research, as this research aims to examine how SDL components mediate relationships between different underlying variables in the context of using GenAI tools in assessment.

Participants and procedures

This study targeted regular undergraduate students aged 20 years or older who were enrolled in the Faculties of Specific Education and Early Childhood Education at Menoufia University. A convenience sampling strategy was employed because it enabled efficient access to eligible participants within the study period (Ahmed, 2024). Data were collected using an online questionnaire administered through Google Forms between May and June 2025.

Eligibility was limited to fourth-year undergraduate students with prior experience using GenAI tools to assess their learning outcomes. Before participating in the survey, all eligible students completed a structured application process to ensure their actual exposure to Generative AI-assisted assessment. This process began with faculty guidance and hands-on training in the educational functions and assessment capabilities of GenAI tools. Following this preparation, students were asked to integrate GenAI tools into authentic assessment activities within their coursework.

Students used GenAI tools to evaluate their learning products according to the assessment criteria and guidelines established by faculty members. This allowed them to identify strengths and weaknesses in their work, receive formative feedback generated by the GenAI tools, and revise and refine their products before final submission. Accordingly, the general artificial intelligence tools served as a supportive assessment tool within real-world educational practice, not as a virtual or simulated technology. Therefore, the questionnaire was only distributed at the end of the academic year, after students had completed these assessment activities, to ensure that all responses reflected the actual experience of assessment supported by GenAI tools.

To further characterize the participants' assessment experience, the questionnaire also asked respondents to identify the GenAI tool they primarily used during the assessment activities. The results indicated that ChatGPT was the most frequently used tools, followed by Google Gemini, then DeepSeek, while a small percentage of participants reported using

other GenAI tools. This suggests that participants' responses were based on practical experience with widely used GenAI tools, rather than on a single platform.

Before administering the questionnaire, the instrument was reviewed to ensure its clarity, relevance, and suitability for the target population. Participants were informed of the study objectives, assured of the confidentiality of their responses, and asked to provide informed consent prior to participation. After data collection, all responses were screened for completeness and validity, resulting in a final sample of 379 valid responses.

Survey instruments

The survey instruments for this research were evaluated using items adapted from established scales to ensure their suitability to the specific context of this research. Specifically, the use of GenAI tools was measured using three (U_GenAI) elements adapted from Liu et al. (2025). The five concepts of SDL were measured using items adapted from Williamson (2007). The components of SDL were measured with twelve elements per component: awareness (AW1 to AW12), learning strategies (SL1 to SL12), learning activities (LA1 to LA12), assessment (EV1 to EV12), and interpersonal skills (IS1 to IS12). LM was measured by four items (MOT1 to MOT4) adapted from Wang et al. (2019). All items were measured using a 5-point Likert scale, which ranges from 1 "never" to 5 "always". DTM mindset was measured using 19 items (DTM1 to DTM19) adapted from Dosi et al. (2018). We used a five-point Likert scale ranging from 1 "strongly disagree" to 5 "strongly agree".

Analytical method

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed as the primary analytical method (Hair et al., 2019). PLS-SEM was selected because of its suitability for examining complex relationships among multiple latent variables and its strong predictive and exploratory capabilities. The method is particularly appropriate for studies that aim to analyze mediation relationships and maximize the explained variance of endogenous constructs. In the context of the current study, PLS-SEM enabled the examination of how awareness, LS, LA, evaluation, and IS mediate the relationships among different underlying variables associated with the use of GenAI tools in assessment. In addition, PLS-SEM is well-suited for handling relatively moderate sample sizes and does not require strict assumptions of data normality. The analysis was performed using SmartPLS 4.0. To address the potential concern of common method bias arising from the use of a single-source, self-reported, and cross-sectional survey design, several procedural and statistical considerations were applied. Procedurally, respondents were assured of anonymity and confidentiality, and participation was voluntary to minimize social desirability bias. In addition, the questionnaire items were carefully adapted from validated

scales and were presented in a clear and non-leading format to reduce response bias. Statistically, the measurement model assessment (Section 4.2) provided initial evidence supporting construct validity and reliability through indicator loadings, Composite Reliability (CR), Average Variance Extracted (AVE), and Heterotrait–Monotrait Ratio (HTMT). These indicators suggest acceptable measurement quality and reduce the likelihood of severe common method distortion. However, given the nature of the research design, the possibility of common method variance cannot be completely ruled out, and this limitation is acknowledged in the interpretation of the results.

Results

Respondent characteristics

Table 1 shows the characteristics of the respondents. 21.90% of the respondents were male, and 70.98% were female. The largest percentage of respondents was in the 20–22 age group, at 84.96%, while the percentage of respondents in the 23–25 age group was 15.04%. The respondents were 52.77% of students in the Computer Teacher program and 47.23% of the Early Childhood Teachers Program. The percentages of respondents varied according to specialization in the secondary (pre-university) stage. The highest percentage was for the science specialization (36.68%), followed by the humanities specialization (35.62%), while the mathematics specialization was 19.79%, and the lowest percentages were for technical institutes (7.92%). Regarding the use of GenAI tools in assessment, ChatGPT came in at 57.52%, followed by Google Gemini at 25.07%, while DeepSeek came in at 13.72%, and another at 3.69%.

Table 1

Respondent characteristics

	Frequency	Percentage(%)
Gender		
Male	110	29.02
Female	269	70.98
Age(Years)		
20-22	322	84.96
23-25	57	15.04
faculties		
Faculty of Specific Education	200	52.77
Faculty of Early Childhood Education	179	47.23
Specialist		
Art	135	35.62
Science	139	36.68
Mathematics	105	19.79
Generative AI tools used		
ChatGPT	218	57.52
Google Gemini	95	25.07
DeepSeek	52	13.72
Others	14	3.69

Validating the measurement model

The validity and reliability of the measurement model were verified using several key criteria: indicator loads, Average Variance Extracted (AVE), Composite Reliability (CR), and Heterotrait–Monotrait Ratio (HTMT). Table 2 shows the loads of the indicators that were first checked to ensure that each element is heavily loaded on its own structure. It is evident that CR values ranging between 0.968 and 0.930 exceed the recommended limit of 0.7 according to Bagozzi and Yi. (1988). Loads exceeding 0.70 are generally considered acceptable, indicating that the element has a strong connection to the underlying structure. In this research, all elements showed loads exceeding the threshold of 0.70.

Table 2

Indicator loadings, AVE, and CR

Variables	Items	Loadings	AVE	CR
Awareness (AW)	AW1	0.741	0.589	0.941
	AW2	0.818		
	AW3	0.815		
	AW4	0.797		
	AW5	0.766		
	AW6	0.793		
	AW7	0.815		
	AW8	0.796		
	AW9	0.798		
	AW10	0.622		
	AW11	0.758		
	AW12	0.749		
Promote _DTM (DTM)	DTM1	0.812	0.607	0.968
	DTM2	0.832		
	DTM3	0.771		
	DTM4	0.760		
	DTM5	0.741		
	DTM6	0.739		
	DTM7	0.781		
	DTM8	0.811		
	DTM9	0.780		
	DTM10	0.782		
	DTM11	0.822		
	DTM12	0.796		
	DTM13	0.778		
	DTM14	0.749		
	DTM15	0.771		
	DTM16	0.811		
	DTM17	0.711		
	DTM18	0.737		
	DTM19	0.732		
Evaluation (EV)	EV1	0.814	0.640	0.963
	EV2	0.777		
	EV3	0.777		
	EV4	0.808		
	EV5	0.823		
	EV6	0.812		
	EV7	0.809		
	EV8	0.819		
	EV9	0.838		
	EV10	0.821		
	EV11	0.789		
	EV12	0.741		
Interpersonal skills (IS)	IS1	0.767	0.603	0.950
	IS2	0.789		
	IS3	0.799		

Variables	Items	Loadings	AVE	CR
Learning activities (LA)	IS4	0.755	0.605	0.950
	IS5	0.805		
	IS6	0.794		
	IS7	0.767		
	IS8	0.655		
	IS9	0.750		
	IS10	0.812		
	IS11	0.796		
	IS12	0.781		
	LA1	0.765		
	LA2	0.778		
	LA3	0.824		
Learning strategies (LS)	LA4	0.803	0.608	0.952
	LA5	0.730		
	LA6	0.732		
	LA7	0.784		
	LA8	0.801		
	LA9	0.746		
	LA10	0.745		
	LA11	0.798		
	LA12	0.701		
	LS1	0.777		
	LS2	0.800		
	LS3	0.812		
Students' learning _MOT (MOT)	LS4	0.767	0.630	0.945
	LS5	0.743		
	LS6	0.749		
	LS7	0.812		
Use_GenAIT (U_GenAI)	LS8	0.785	0.814	0.930
	LS9	0.747		
	LS10	0.771		
	LS11	0.627		
	LS12	0.773	0.814	0.930
	MOT1	0.783		
	MOT2	0.706		
	MOT3	0.809		
	MOT4	0.835	0.814	0.930
	U_GenAI1	0.902		
	U_GenAI2	0.907		
	U_GenAI3	0.890		

In addition, the AVE values ranged between 0.589 and 0.814, higher than 0.5, indicating sufficient convergent validity (Chin & Todd, 1995). This means that more than half of the variance in the indices is attributable to compositions. The external loads of the individual elements range between 0.622 and 0.907, with all elements exceeding the minimum acceptable limit of 0.7 (Hulland, 1999), except for two indicators (AW10/LS11), which are

slightly lower. While both the overall reliability and convergent validity of the measurement model are achieved.

Table 3

Correlation ratio between HTMT

Structure	AW	DTM	EV	IS	LA	LS	MOT
U_GenAI	0.364	0.380	0.334	0.399	0.370	0.405	0.395
MOT	0.674	0.801	0.730	0.803	0.736	0.800	
LS	0.697	0.830	0.835	0.849	0.793		
LA	0.650	0.672	0.720	0.751			
IS	0.758	0.814	0.771				
EV	0.638	0.841					
DTM	0.722						

The validity of the discrimination was assessed using the HTMT standard. As shown in Table 3, all HTMT values were below the threshold of 0.85 (Henseler et al. 2015), confirming that the structures were sufficiently distinct from each other. Taken together, these results demonstrate that the measurement model is reliable and valid, providing a strong basis for subsequent analysis.

Structural model

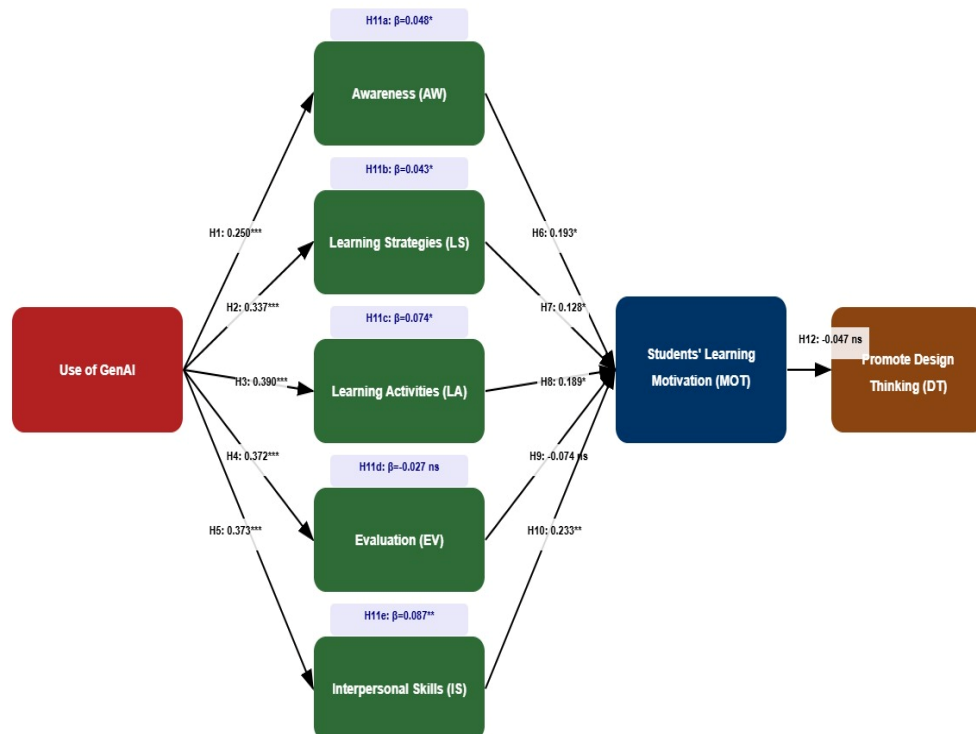
The structural model was evaluated to assess the relationships between structural variables, Figure 2, and Table 4 summarizes these results.

Table 4
Structural model evaluation

Hypothesis	Relationship	Std. Beta	Std. Error	t-value	p-value	Decision	VIF
H1	U_GenAI -> AW	0.2500	0.0567	4.4076***	0.000	Supported	1.0000
H2	U_GenAI -> LS	0.3370	0.0575	5.8564***	0.000	Supported	1.0000
H3	U_GenAI -> LA	0.3902	0.0585	6.6713***	0.000	Supported	1.0000
H4	U_GenAI -> EV	0.3715	0.0610	6.0884***	0.000	Supported	1.0000
H5	U_GenAI -> IS	0.3732	0.0585	6.3844***	0.000	Supported	1.0000
H6	AW -> MOT	0.1929	0.0827	2.3334*	0.050	Supported	1.8845
H7	LS -> MOT	0.1284	0.0849	2.0026*	0.050	Supported	2.3669
H8	LA -> MOT	0.1889	0.0841	2.2463*	0.050	Supported	2.9464
H9	EV -> MOT	0.0737	0.0771	0.9566	0.962	Not supported	2.8851
H10	IS -> MOT	0.2328	0.0817	2.8491**	0.010	Supported	2.4636
H11	MOT -> DTM	0.0466	0.0514	-0.9074	0.951	Not supported	1.0000
H11a	U_GenAI -> AW -> MOT	0.0482	0.0240	2.0097*	0.050	Supported	—
H11b	U_GenAI -> LS -> MOT	0.0433	0.0294	2.0094*	0.050	Supported	—
H11c	U_GenAI -> LA -> MOT	0.0737	0.0354	2.0823*	0.050	Supported	—
H11d	U_GenAI -> EV -> MOT	0.0274	0.0293	0.9334	0.945	Not supported	—
H11e	U_GenAI -> IS -> MOT	0.0869	0.0336	2.5890**	0.010	Supported	—

Not: *P<0.05, **P<0.01, ***P<0.001

Figure 2
Structural model results (PLS-SEM).



Relationship between the use of GenAI tools and SDL components

The analysis covers the testing of Hypotheses H1–H5. Analysis revealed significant positive relationships between the use of GenAI tools (U_GenAI) and the components of SDL: AW, LS, LA, EV, and IS. Specifically, the use of GenAI tools was found to have a significant positive impact on AW (H1: $\beta = 0.250$, $t = 4.4076$, $p < 0.001$), LS (H2: $\beta = 0.3370$, $t = 5.8564$, $p < 0.001$), LA (H3: $\beta = 0.3902$, $t = 6.6713$, $p < 0.001$), EV (H4: $\beta = 0.3715$, $t = 6.0884$, $p < 0.001$), and IS (H5: $\beta = 0.3732$, $t = 6.3844$, $p < 0.001$). This reflects how GenAI tools enhance students' awareness, LS, LA, IS, and evaluation.

The relationship between the components of SDL and LM

On the other hand, the analysis covers the testing of Hypotheses H6–H10. The results showed that LM (MOT) is positively affected by AW (H6: $\beta = 0.1929$, $t = 2.3334$, $p < 0.05$), LS (H7: $\beta = 0.1284$, $t = 2.0026$, $p < 0.05$), LA (H8: $\beta = 0.1889$, $t = 2.2463$, $p < 0.05$), and IS (H10: $\beta = 0.2328$, $t = 2.8491$, $p < 0.01$). While there are non-significant findings of the effect of EV on LM (H9: $\beta = 0.0737$, $t = -0.9566$, $p = 0.9620$). This reflects that GenAI tools may make students more self-critical when being assessed. This highlights the mediating role of LM as a crucial link between SDL and the use of GenAI tools.

The relationship between LM and DTM.

Regarding the relationship between LM and DTM, the MOT $\rightarrow$ DTM pathway analysis showed that it was not statistically significant (H11: $\beta = -0.0466$, $t = 0.9074$, $p = 0.951$). This means that there is no strong positive relationship between LM and DTM.

The effect of mediating SDL components on the relationship between the use of GenAI tools and LM.

The analysis covers the testing of Hypotheses H11a–H11e. The results showed that IS significantly mediated the relationship between LM and the use of GenAI tools (H11e: $\beta = 0.0869$, $t = 2.5890$, $p < 0.01$), followed by LA (H11c: $\beta = 0.0737$, $t = 2.0823$, $p < 0.05$), as did AW (H11a: $\beta = 0.0482$, $t = 2.0097$, $p < 0.05$), along with LS (H11b: $\beta = 0.0433$, $t = 2.0094$, $p < 0.05$). In contrast, the EV did not mediate the relationship between the use of GenAI tools in assessment and LM (H11d: $\beta = 0.0274$, $t = 0.9334$, $p = 0.945$). The values of the Variance Inflation Coefficient (VIF) for all structural variables fell from 1.000 to 2.676, which is within the acceptable range, indicating that there are no serious concerns about multicollinearity.

Discussion

While GenAI tools weave a web into many human aspects through their generative ability to mimic human-generated content, they promote a more encouraging and interactive learning experience among students. It is not just a tool; it functions as a generative virtual assistant, raising concerns about its impact on perception and DTM. The academic community claims that these advanced tools may undermine the components of SDL for students through a decline in personal control and over-reliance on them for skills development, thus reducing authentic human interactions (Bin-Nashwan et al. 2023). In this research, and in response to the gaps in the literature, the present study sought to examine the associations between GenAI tool use and students' SDL components. Another objective that this research sought to verify was whether the components of SDL could fuel students' LM and ultimately their DTM.

The relationship between the use of GenAI tools and SDL components

H1: The use of GenAI tools in assessment has a positive impact on student awareness.

H1 1a: Awareness mediates the relationship between the use of GenAI tools in assessment and students' LM.

The results of the model shown in Table 4 indicate that the use of GenAI tools had a direct and significant impact on all components of SDL, reinforcing the growing evidence that GenAI tools can play a catalytic role in the development of SDL components. The analysis results showed that the use of GenAI tools was positively associated with student awareness by giving them more self-monitoring. This means that the use of GenAI tools helps to raise the level of cognitive and motivational awareness among students and enables them to make educational decisions. On the other hand, this means that GenAI tools can design learning experiences that increase the student's ability and awareness to choose learning methods, topics, and pace. Conversely, the unconscious use of GenAI tools may lead to over-reliance that weakens critical thinking and reduces self-directed awareness (Zhai et al. 2024). The strong interaction between awareness and the use of GenAI tools obtained in our research demonstrates the need for technology-based education, while maintaining students' awareness in learning. Therefore, there is a need to integrate guidance strategies that support the use of GenAI tools in relation to awareness and thinking, rather than as a replacement for them.

The recent research trend indicates that self-directed awareness forms the basic mediator between employing GenAI tools and achieving motivation. This is consistent with the conclusion confirmed by previous research (Bozkuş & Canoğulları, 2025), although it is still limited. Interestingly, it was found that awareness significantly mediates the correlation between the use of GenAI tools and students' LM, underscoring its importance

in enabling students to take control of their learning process and enhancing their sense of self-efficacy and achievement. This means that students become more able to understand their educational needs, set their goals, and assess their own progress, which enhances their intrinsic motivation to learn. In other words, the use of GenAI tools does not in itself increase motivation to learn, but the effectiveness lies in being aware of how to use it intelligently as a tool for generating knowledge, not as a means to obtain ready-made assessments.

H2: The use of GenAI tools in assessment has a positive impact on students' LS.

H11b: LS mediate the relationship between the use of GenAI tools in assessment and students' LM.

Analysis also showed that students' use of GenAI tools has a positive impact on LS. This means that GenAI tools influence how students organize their learning process and apply effective LS. These tools provide suggested customized learning paths, reducing cognitive load and facilitating the adoption of strategies such as advanced planning and time-division (Kim et al. 2025). Furthermore, support for GenAI tools in relation to metacognitive practices is associated with greater learner awareness of learning processes and stronger self-monitoring and self-assessment abilities, which may be linked to broader and more effective application of self-LS (Yang & Xia, 2023). However, this suggests the possibility of improving self-LS through the use of GenAI tools, especially since LS have a mediating effect on the correlation between GenAI tools and LM. This indicates that the effect of using GenAI tools in enhancing the motivation to learn does not only occur directly, but is mediated through self-LS employed by students while interacting with these tools. Generative tools help students organize knowledge, plan, and self-monitor, which are essential practices for promoting SDL strategies (Chugh et al. 2025). This shows that LS represent a cognitive and emotional link between technology and motivation, enabling students to direct GenAI tools towards achieving their educational goals with greater self-awareness and self-efficacy.

H3: The use of GenAI tools in assessment has a positive impact on student LA.

H11c: LA mediate the relationship between the use of GenAI tools in assessment and students' LM.

It was found that the use of GenAI tools exerts a positive influence on student LA in SDL. Student LA can be enhanced by adopting GenAI tools in SDL processes, consistent with the conclusions (Owan et al. 2025). This suggests that adopting GenAI tools in academic environments can support active student participation in learning processes such as generating assessments, asking exploratory questions, and organizing knowledge systematically, thereby promoting SDL activities. The tools also provide interactive learning environments that enable students to employ LS appropriate to their individual goals, which increases the effectiveness of LA and makes them more independent.

Therefore, it appears that the positive impact of GenAI tools is mainly focused on activating self-LA, which represents the essence of SDL and promotes motivation. In addition, an effect of LA was found after testing the mediating role relationship in the relationship between the use of GenAI tools and students' LM. This means that the use of GenAI tools is done by activating students' self-LA, such as planning, self-monitoring, and self-evaluation (Wu & Chiu, 2025). Therefore, GenAI tools have the potential to provide personalized feedback and interactive features, which may help students feel valued and may be associated with higher levels of self-directed activities, as an essential part of maintaining student motivation (Mohamed et al., 2025). Therefore, increasing LM depends directly on the extent to which SDL activities are activated during the use of GenAI tools, which underscores the need to integrate these tools in conscious and directed ways within educational environments to support SDL.

H4: The use of GenAI tools in assessment has a positive impact on student evaluation.

H11d: Evaluation mediates the relationship between the use of GenAI tools in assessment and students' LM.

The research results revealed that the use of generative GenAI tools has a positive impact on evaluation as a component of SDL. In this context, the study by Jansen et al. (2024) indicates that GenAI tools enable students to conduct continuous assessment by providing immediate feedback, suggesting performance improvements, and comparing benchmark results, thereby enhancing the ability to think reflectively and make conscious decisions. Furthermore, the study by Rao and Suhasini (2025) indicates that integrating these tools supports adaptive self-assessment, where students can modify their LS based on the results of immediate assessment, thus increasing the effectiveness of SDL. Therefore, it appears that GenAI tools are associated with students' abilities for systematic self-assessment.

However, although this work revealed the potential for improving self-assessment through the use of GenAI tools, self-assessment did not have a mediating effect on the association between the use of GenAI tools and LM. The reason is likely due to students' excessive reliance on the generative outputs of GenAI tools without sufficient practice of self-reflection or critical review, which reduces the effectiveness of self-assessment as a cognitive mechanism that stimulates motivation (Fan et al. 2025). The absence of the mediating effect may also be related to the nature of the use of GenAI tools, which often focus on producing assessments and content rather than supporting reflective thinking. Gerlich's study (2025) indicates a significant negative relationship between the frequent use of GenAI tools and critical thinking. On the other hand, study Cronin-Golomb and Bauer (2023) indicate that motivation is more influenced by factors such as active engagement and self-LS in SDL rather than purely evaluative processes. In addition, the phenomenon of cognitive offloading may cause students to rely on the outputs of GenAI

tools instead of conducting regular internal assessments, which weakens the ability of self-assessment to act as a mediator between technology and LM (Gerlich, 2025).

The non-significant mediating role of self-evaluation may be explained by the nature of GenAI-supported learning environments, where students increasingly rely on immediate automated feedback rather than engaging in deep reflective evaluation of their own learning processes. Although self-evaluation is considered a core component of self-directed learning, its effectiveness depends on learners' metacognitive engagement and reflective judgment abilities (Panadero, 2017). In GenAI-supported contexts, externally generated feedback may partially substitute for internal evaluative processes, thereby weakening the motivational influence of self-evaluation. This finding is also consistent with prior research suggesting that automated feedback is not necessarily associated with stronger self-regulated learning or intrinsic motivation unless it explicitly promotes reflective and self-monitoring practices (Nicol & Macfarlane-Dick, 2006). Moreover, motivation in digital learning environments may be more strongly influenced by adaptive support, learning autonomy, and interactive engagement than by self-evaluative processes alone (Zimmerman, 2002). Accordingly, the current finding highlights a potentially important cautionary implication within GenAI-in-HE research: integrating GenAI tools may not automatically support all dimensions of self-directed learning equally, particularly those requiring sustained reflective and metacognitive involvement.

H5: The use of GenAI tools in assessment has a positive impact on students' IS.

H11e: IS mediate the relationship between the use of GenAI tools in assessment and students' LM.

The results of the model structure verification in this research indicate that the use of GenAI tools has a positive and significant impact on students' IS. This positive association may be attributed to the ability of GenAI tools to support students' time management and effort organization processes. In addition, these tools provide students with an interactive learning environment that supports independence, decision-making ability, and critical thinking in learning (Wu & Chiu, 2025; Mohamed et al., 2025). In this context, the study of Fan et al. (2025) indicates that regular interaction with GenAI tools enhances self-efficacy and self-discipline, which is reflected in the development of important IS such as academic stress management. On the other hand, an effect was found after testing the mediating role of IS in the relationship between the use of GenAI tools and students' LM. When GenAI tools are integrated into learning environments, the direct impact on motivation is not only a result of interacting with them, but also occurs through the development of a set of interpersonal, organizational, and emotional skills that contribute to raising self-awareness, controlling behavior, and managing effort during learning (Bai & Wang, 2025). IS act as a cognitive-emotional bridge that transforms the student's technological experience into an intrinsic motivation for learning, as GenAI tools enable him to practice independence in

learning and plan SDL paths. Studies also show that GenAI tools develop skills such as critical thinking, communication, and self-discipline, making students more willing to actively engage in learning (Wu & Chiu, 2025; Chugh et al., 2025). Therefore, it can be said that the motivational effect of GenAI tools is largely activated by IS that contribute to transforming technological use into a learning motive.

The relationship between the components of SDL and LM, hypotheses (H6 – H10).

The results also show that motivation was significantly influenced by IS and LA, reflecting the intrinsic importance of interpersonal competencies and active interaction in supporting intrinsic motivation to learn within SDL environments supported by GenAI tools. Theoretically, this result supports the self-determination theory frameworks developed by Deci & Ryan (2000), which assert that developing communication, collaboration, and empathy skills as essential components of IS contributes to meeting learners' needs for belonging, competence, and autonomy, thereby enhancing their intrinsic motivation to learn. Studies by (Bai & Wang, 2025; Fan et al., 2025) show that GenAI tools, when integrated with interactive LA, create an environment that encourages critical thinking, collaboration, and problem-solving, which are cognitive and social processes directly related to increased LM. Cronin-Golomb & Bauer (2023) indicate that SDL becomes more effective when students develop social interaction and self-regulation skills with LA that stimulate independence and active participation. Accordingly, the result may be interpreted as reflecting the activation of IS and interactive LA associated with stronger emotional and cognitive engagement in learning, which may relate to higher levels of intrinsic motivation toward acquiring knowledge and achieving educational goals. Meanwhile, the impact of LS and awareness was moderate, indicating that these factors act as supporting elements but are not the main determinant of LM. Conversely, there appears to be a negative effect of assessment on motivation, which is consistent with some literature indicating that rigorous or unsupported self-assessment may lead to a decrease in learners' motivation as a result of feelings of self-criticism or academic anxiety (Ryan & Deci, 2020).

The relationship between LM and DTM, hypothesis(H11).

Our findings indicate the absence of a significant relationship between LM and DTM. Although previous literature indicates a positive relationship between intrinsic motivation and the ability to DTM (Henriksen et al. 2017), this research suggests that the relationship may not be direct. Other factors may mediate, such as creativity, engagement in tasks, or even students' prior experience with DTM methodologies. In light of the theoretical frameworks of motivation-based and creative learning from the perspective of Deci &

Ryan's (2000) self-report theory, intrinsic motivation is usually associated with open-minded thinking processes, as it is influenced by mediating factors such as environmental support and LS. Therefore, in the case of DTM, which requires a combination of analysis, innovation, and experimentation, motivation alone may not be sufficient to stimulate design performance unless a learning environment is available that encourages risk-taking and safe experimentation (Razzouk & Shute, 2012). Study Avsec (2023) has shown that DTM relies more on higher cognitive skills and self-regulation than on general motivation to learn. Even highly motivated students may lack the cognitive tools or creative strategies necessary to effectively apply DTM processes. Similar results from (Bai & Wang, 2025; Fan et al., 2025) show that the use of GenAI tools can be associated with higher levels of LM without necessarily improving DTM, indicating that DTM is a relatively independent skill that requires systematic training and practical application beyond the limits of intrinsic motivation.

The finding of no statistically significant relationship between DTM and LM can be discussed in light of several theoretical and methodological interpretations related to the nature of design thinking and the characteristics of learning environments supported by GenAI tools. While many studies implicitly assume that higher motivation automatically leads to improved design thinking practices, the results of the current study suggest that the development of DTM may not depend directly on motivation levels as much as it depends on more complex cognitive, procedural, and technical requirements. This finding is consistent with the literature that emphasizes design thinking as a multidimensional construct requiring analytical, problem-solving, divergent thinking, experimentation, empathy, and iteration skills—processes that may not be influenced by motivation alone (Razzouk & Shute, 2012). This result can also be explained by the fact that GenAI tools may reduce students' reliance on intrinsic motivation while performing design tasks. These tools provide immediate support, idea generation, and continuous guidance, enabling students to complete tasks even with varying levels of motivation. In this sense, some learning processes may shift from being associated with intrinsic motivation to being technologically supported by GenAI tools, as indicated by recent studies examining the transformation of learner roles within AI-assisted environments (Kasneci et al., 2023; Tlili et al., 2023).

On the other hand, the current result may reflect the nature of DTM as a long-term cognitive and behavioral orientation. While motivation to learn is often influenced by situational and contextual factors that may be temporary, building a DTM requires extended experiences and repeated practices linked to a learning culture, project engagement, and continuous exposure to authentic design tasks (Carlgren et al., 2016). Therefore, the absence of a statistically significant relationship may indicate that developing DTM requires specialized instructional designs that go beyond simply

increasing motivation levels. This finding is an important scientific addition to the literature on artificial intelligence in higher education, as it offers a cautionary perspective against the growing assumption that integrating GenAI tools and motivating students will automatically lead to the development of higher-order thinking skills, including DTM. The current findings suggest that the effective use of GenAI in higher education should not be limited to enhancing interaction or motivation, but should also include designing learning activities that directly focus on design processes, complex problem-solving, reflective thinking, and structured creative practice. Therefore, this study calls for a re-evaluation of some of the overly optimistic assumptions in the educational GenAI literature and emphasizes that advancements in DTM may require more profound educational interventions than simply providing AI-enabled learning environments.

On the other hand, DTM represents a way of reasoning under conditions of uncertainty rather than merely a set of procedural skills (Groeger & Schweitzer, 2020). Schön (1983) emphasizes DTM as an adaptive and metacognitive orientation shaped by the ongoing reinterpretation of problems and evolving feedback (Dorst, 2019). Extending this perspective, Dorst (2015) highlights “design framing” as the ability to construct and reframe problem situations, reinforcing cognitive flexibility and tolerance for ambiguity as central dimensions of DTM (Cross, 2011; Dorst, 2015). Collectively, these perspectives position DTM as a higher-order cognitive-dispositional construct grounded in design epistemology rather than a purely motivational outcome (Schön, 1983; Lawson, 2006). Accordingly, the non-significant relationship between learning motivation (LM) and DTM may suggest that motivational disposition alone is insufficient to explain variation in design thinking orientation, which appears to depend more strongly on sustained engagement in reflective practice, iterative problem framing, and cognitively demanding design processes.

Furthermore, contrary to our initial expectations, the structural relationship between learning motivation and DTM was not statistically significant. While AI-powered assessment can increase student engagement and motivation by providing immediate, personalized, and formative feedback, these motivational gains do not necessarily translate into DTM development. DTM represents a higher level of cognitive and metacognitive competence that goes beyond learners' willingness to engage in learning. It requires sustained engagement with real-world design challenges involving empathy, iterative thinking, experimentation, prototyping, reflection, and collaborative problem-solving (Avsec & Ferk Savec, 2022). Therefore, learning motivation may act as a facilitator of engagement, but it is unlikely to serve as a direct predictor of DTM in the absence of educational experiences specifically designed to cultivate a design-thinking mindset (Huang, et al.,2025).

This interpretation aligns with a growing body of empirical research on generative AI-enabled learning environments. For example, Huang (2024) demonstrated that significant

improvements in students' creative and design thinking emerged when generative AI was integrated into a co-organized learning environment that systematically supported collaboration, reflection, and iterative design processes. It is important to note that these notable gains were not solely attributable to the availability of GenAI tools, but rather to the instructional design that integrated these tools into real-world learning activities.

The current findings are consistent with the work of Hao et al. (2026), who argued that the educational benefits of AI do not arise automatically from the use of the technology itself. Rather, they showed that students' creativity is influenced by their attitudes toward AI and their digital competencies, suggesting that AI-assisted learning outcomes are shaped by multiple learner- and contextual factors. This perspective helps explain why learning motivation alone was not a strong predictor of DTM in this study. While motivation may encourage students to engage with AI-assisted assessment, developing DTM likely requires additional competencies and pedagogical conditions that go beyond mere motivational readiness.

Similarly, recent empirical evidence has shown that AI-enhanced design-based learning environments can foster students' DTM when AI is integrated into authentic design activities and collaborative learning processes. Furthermore, recent reviews emphasize that the educational value of generative AI depends on how it is pedagogically employed to support self-regulation, feedback, reflection, and higher-order thinking, rather than solely on the use of the technology itself (Saritepeci & Yildiz Durak, 2024). Therefore, the current findings suggest that although general AI-assisted assessment may improve students' self-directed learning processes, additional educational mechanisms are needed before these gains can be translated into measurable improvements in design thinking.

This interpretation is further supported by a recent systematic review by Xia et al. (2025), which concluded that generative AI contributes most effectively to higher-order learning outcomes when it acts as a pedagogical support that fosters SDL, reflection, formative feedback, and iterative problem-solving. The review also emphasized that improvements in SDL or learning motivation should not be expected to automatically translate into complex competencies such as DTM unless appropriate instructional mechanisms are intentionally integrated into the learning environment. Therefore, the absence of a statistically significant direct relationship between learning motivation and DTM in this study should not be interpreted as evidence of the ineffectiveness of GenAI tools in promoting DTM. Rather, it suggests that motivational improvements resulting from generative AI-assisted assessment alone may not be sufficient to develop DTM unless they are complemented by authentic design experiments, collaborative inquiry, and structured pedagogical support. Accordingly, the current findings contribute to the emerging literature on artificial intelligence by highlighting that the educational impact of next-generation AI on DTM is mediated not only by the learner's characteristics and orientation to the use of

GenAI tools, but also by the instructional design that governs how next-generation AI is integrated into assessment and learning activities.

Implications

Theoretical implications

This research reinforces theoretical efforts to understand the role of GenAI tools in shaping SDL frameworks among students. Empirical support from this research regarding the application of SDL in virtual learning environments can be obtained by examining how GenAI tools influence the core components of SDL, including awareness, LS, LA, evaluation, and IS. The findings indicate that GenAI tools can effectively support SDL needs by providing adaptive guidance, immediate feedback, and personalized learning experiences, thereby enhancing student motivation and engagement. This study may be among the first to empirically investigate the impact of GenAI tools on SDL components and the mediating role of these components in the relationship between the use of GenAI tools and students' learning motivation. In addition, the study contributes theoretically by examining how students' LM, strengthened through SDL components supported by GenAI tools, may contribute to the development of DTM. This, the absence of a significant relationship between motivation and DTM suggests that DTM development may rely more heavily on cognitive and technical instructional requirements, problem-solving processes, and task design characteristics than on motivational factors alone.

Practical implications

The research provides several implications for HE officials seeking to support learning outcomes by integrating GenAI tools in ways that reinforce the components of SDL and student motivation. Practically, learning administrators should design and implement curriculum guidelines that embed GenAI tools to create personalized, interactive learning experiences that strengthen students' components of SDL. Collaboration between HE officials and content developers is therefore essential to ensure that these components are consistently integrated across academic preparation levels. It is also recommended that faculty participate in professional development programs focused on the effective pedagogical use of GenAI tools. These programs should include clear methods for leveraging GenAI tools to support the core elements of SDL. Moreover, establishing institutional policies, regulations, and frameworks that facilitate the adoption of GenAI tools has become a necessity for creating a more connected and supportive learning environment. Implementing GenAI tools that enable students to personalize their learning—by selecting preferred methods, topics, and pacing—requires continuous evaluation and adaptation based on student feedback. This highlights the role of

educational technology developers and AI specialists in ensuring effective integration. Although findings show no relationship between motivation and DTM, this necessitates designing curricula and assessment activities that promote DTM independently of motivational levels.

Conclusions and future research directions

This research showed that the use of GenAI tools in assessment has a significant impact on the SDL framework with its five components. Future studies could conduct research to identify the effects of using GenAI tools on students' autonomy, self-efficacy, and prior experiences. In addition to exploring the relationship between the use of tools and the educational context, and enhancing student attendance and participation in learning. The current study found that all components of SDL influence the relationship between the use of GenAI tools and motivation, with the exception of evaluation. There was no statistically significant correlation between the effect of evaluation on motivation as a mediating variable. Therefore, future studies should investigate the effects of assessments of GenAI tools, which may sometimes be rigorous or unsupported, and their relationship to student motivation and academic anxiety. The study was conducted on students enrolled in a HE institution, with female participants comprising more than 70% of the male participants. Researchers conducting future research should include a larger proportion of males and stakeholders, such as faculty members and parents. Faculty members, administrators, and parents can all provide a comprehensive view that leads to improved decision-making and policy skills. Future studies should consider examining higher-order thinking skills, components of SDL, and students' self-efficacy in the context of education in the age of GenAI tools. DTM and SDL are vital life skills for students when they enter the job market. Therefore, further investigations should assess how the use of GenAI tools can help students develop their prior life skills. According to the results of the current study, there was a lack of relationship between motivation and DTM. Future studies may conduct further research to explore mediating or modifying variables that may explain this gap, and to arrive at broader explanatory models that include the cognitive and emotional structure of students. This research is subject to potential bias due to the use of a single-source, self-reported, cross-sectional survey design, which may amplify observed relationships between variables. Although steps have been taken to ensure the validity of the measurements, this limitation should be considered, and future research is encouraged to use multi-source and longitudinal designs to enhance the robustness of the results and reduce methodological bias.

Abbreviations

SDL: Self-directed learning; DTM: design thinking mindset; GenAI: Generative artificial intelligence; HE: higher education; LM: learning motivation; LS: learning strategies; LA :learning activities; IS: interpersonal skills; AVE: Average Variance Extracted; CR: Composite Reliability; HTMT: Heterotrait–Monotrait Ratio;

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Author's contributions

The authors is responsible for the whole manuscript. The authors read and approved the final manuscript.

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Declarations

Competing interests

All financial and non-financial competing interests must be declared in this section. If it is not applicable, please put the following statement in this section: "The authors declare that they have no competing interests."

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