

Beyond Faster Learning: How GenAI Learning Efficiency Translates into Effective Learning Outcomes

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Abstract

Generative artificial intelligence (GenAI) can make learning faster and less demanding, but greater efficiency does not necessarily result in better learning. This study examines how GenAI learning efficiency is translated into effective learning outcomes among higher-education students in India. GenAI Learning Efficiency (GLE) is conceptualized as a higher-order construct comprising learning time efficiency, cognitive effort efficiency, learning task efficiency, and knowledge access efficiency. Drawing on Cognitive Load Theory and Self-Regulated Learning theory, the study examines cognitive engagement and self-regulated learning as parallel mechanisms connecting GLE with effective learning outcomes. Data were collected from 548 undergraduate and postgraduate students with prior experience using GenAI for academic purposes and analysed using PLS-SEM. The findings show that GLE strengthens both cognitive engagement and self-regulated learning, which subsequently contribute to effective learning outcomes. Both mechanisms mediate the relationship between GLE and learning outcomes, while a smaller direct effect remains. The study shows that the educational value of GenAI lies not simply in making learning easier or faster, but in whether learners use the resulting efficiency to engage more deeply and regulate their learning effectively.

Keywords: Generative AI; GenAI Learning Efficiency; Cognitive Engagement; Self-Regulated Learning; Effective Learning Outcomes; Higher Education

1. Introduction

Generative artificial intelligence (GenAI) is becoming part of how university students learn. Tools such as ChatGPT and other large language model-based applications allow students to obtain explanations, summarize complex material, generate examples, organize ideas, receive feedback, and explore solutions within seconds. These capabilities have created considerable interest in the educational value of GenAI, with emerging evidence showing potential benefits for academic performance, higher-order thinking, engagement, and learning support (Aboramadan et al., 2024; Dai & Liu, 2024). Yet one of the most immediate changes introduced by GenAI may be more basic: it changes the efficiency of the learning process itself. Tasks that previously required considerable searching, organizing, and processing can now be supported through a single conversational interface.

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Greater efficiency, however, does not necessarily mean better learning. A student may find an explanation more quickly, complete an academic task with fewer steps, or expend less mental effort without necessarily developing deeper understanding. This creates an important tension in GenAI-supported education. On one side, reducing unnecessary demands can leave students with more time and cognitive capacity for meaningful learning. On the other, if efficiency is achieved by transferring too much of the thinking process to AI, students may complete tasks efficiently without engaging sufficiently with what they are learning. Recent research reflects this tension. GenAI-supported learning has been associated with improved performance and reduced mental effort (Kantaros, 2026; Shehawy & Faisal Ali Khan, 2026; Zhai et al., 2024), while other studies caution that easier task performance does not automatically indicate stronger metacognitive awareness or independent cognitive processing (Urban et al., 2024). The educational issue is therefore not simply whether GenAI makes learning easier, but what happens to learning when it does.

Cognitive Load Theory (CLT) provides one explanation for this issue. Human working memory has limited capacity, and learning can improve when unnecessary processing demands are reduced so that cognitive resources remain available for learning-relevant activity (Sweller, 1988). GenAI may serve this function by simplifying difficult explanations, organizing information, providing immediate clarification, and reducing time spent navigating fragmented sources. However, CLT alone cannot fully explain how students use the resources released through these efficiencies. Self-Regulated Learning (SRL) theory complements this perspective by emphasizing learners' active role in setting goals, selecting strategies, monitoring understanding, and evaluating their progress (Seufert, 2018; Tabassum et al., 2024). Recent research suggests that GenAI can support different stages of self-regulated learning, but its benefits depend partly on whether learners maintain agency and metacognitive control over the learning process (Zhou, 2026).

Building on these perspectives, this study introduces GenAI Learning Efficiency (GLE) as a multidimensional higher-order construct. Rather than equating efficiency only with speed, GLE is conceptualized through four dimensions: Learning Time Efficiency (LTE), Cognitive Effort Efficiency (CEE), Learning Task Efficiency (LTAE), and Knowledge Access Efficiency (KAE). These dimensions capture whether GenAI helps learners use time more efficiently, reduce unnecessary cognitive expenditure, perform learning tasks with less procedural friction, and reach relevant knowledge and explanations more efficiently. This distinction is important because GenAI may influence several learning resources simultaneously, and treating efficiency as a single general perception can obscure these different mechanisms.

Although research on GenAI in education is expanding rapidly, existing studies have largely examined outcomes such as adoption, academic performance, engagement, cognitive load, perceived usefulness, and self-regulated learning separately (Abid, 2025; Sheikh et al., 2026). Comparatively less attention has been given to integrating different forms of learning efficiency and explaining how efficiency gains are converted into effective learning outcomes. This leaves an important theoretical gap. Knowing that GenAI saves time or reduces mental effort tells us little about whether students use the released resources to think more deeply, regulate their learning more effectively, or simply finish their work sooner.

The present study addresses this gap by examining cognitive engagement and self-regulated learning as parallel mediating mechanisms between GLE and Effective Learning Outcomes (ELO). Cognitive engagement captures the extent to which students actively process, connect, question, and apply learning material, whereas SRL captures how they plan, monitor, and control their learning. Bringing these mechanisms together allows the study to distinguish between technological efficiency and the learner processes required to turn that efficiency into meaningful educational outcomes.

The study examines these relationships among higher-education students in India, a large and diverse educational environment in which GenAI is becoming increasingly relevant to students across academic disciplines. The study makes three main contributions. First, it develops a multidimensional conceptualization of GenAI Learning Efficiency. Second, it integrates CLT and SRL theory to connect the resource and agency perspectives of GenAI-supported learning. Third, it explains the process through which efficiency may become effective learning by identifying cognitive engagement and self-regulation as two complementary pathways. In doing so, the study shifts the discussion from whether GenAI makes learning easier to a more consequential question: how can the efficiencies created by GenAI be converted into genuine learning gains?

2. Literature Review and Hypothesis Development

2.1 GenAI Learning Efficiency: Theoretical Foundation

Generative artificial intelligence (GenAI) is changing the learning process not only by providing information but also by changing how students allocate time, effort, and cognitive resources. Unlike conventional digital resources, GenAI can respond to questions, simplify complex material, generate examples, summarize information, and provide iterative explanations within a single interaction. These capabilities create opportunities for students to perform learning activities more efficiently (Gadi et al., 2026; Gibreel, 2025). Recent experimental evidence supports this potential (Deng et al., 2024), in a systematic review and meta-analysis of 69 experimental studies, found that ChatGPT-supported learning improved academic performance and higher-order thinking while reducing mental effort. More recent meta-analytic evidence similarly indicates generally positive learning outcomes among undergraduate students using ChatGPT, although effects vary across learning contexts and implementation conditions.

However, making learning easier or faster does not necessarily mean that learning becomes more effective. Cognitive Load Theory (CLT) provides an important explanation for this distinction. CLT recognizes the limited capacity of working memory and argues that learning can be improved when unnecessary cognitive demands are reduced, allowing available cognitive resources to be directed toward processing information relevant to learning (Skulmowski, 2024). Applied to GenAI, this suggests that AI can improve learning efficiency when it removes avoidable processing demands, but not when it replaces cognitive activity that learners themselves need to perform. Indeed, experimental research shows that ChatGPT can make complex problem solving feel easier and require less mental effort, while also raising

questions about learners' ability to accurately evaluate their own performance (Kumar et al., 2026; Zubair & Khan, 2025).

Building on this reasoning, the present study conceptualizes GenAI Learning Efficiency (GLE) as a higher-order construct comprising four complementary dimensions: Learning Time Efficiency (LTE), Cognitive Effort Efficiency (CEE), Learning Task Efficiency (LTAE), and Knowledge Access Efficiency (KAE). Rather than assuming that these dimensions have already been established as a unified scale, the present study proposes them as distinct ways through which GenAI may make the learning process more resource-efficient.

2.2 Dimensions of GenAI Learning Efficiency

Learning Time Efficiency (LTE) refers to the extent to which GenAI allows learners to achieve learning-related objectives in less time. Students can obtain explanations, summaries, examples, comparisons, and clarification through a conversational interface rather than repeatedly searching and integrating multiple information sources. Studies of higher-education students identify time saving, rapid information retrieval, and instant feedback among the perceived benefits of GenAI use (Gadi et al., 2026). Evidence from Saudi higher education similarly shows that students frequently use GenAI to clarify concepts, summarize academic materials, generate ideas, and obtain immediate assistance, with ease of access and time saving reported among its major benefits. These efficiencies are educationally relevant because time released from routine information-search and processing activities can potentially be redirected toward more meaningful learning activities.

Cognitive Effort Efficiency (CEE) refers to the extent to which GenAI reduces cognitive expenditure that is unnecessary for accomplishing a learning objective. This dimension follows directly from CLT. When students struggle with unnecessarily complicated explanations, information organization, or procedural requirements, limited working-memory resources may be consumed without contributing substantially to knowledge construction (Herzallah et al., 2025; Paas et al., 2010; Skulmowski, 2024). GenAI can potentially reduce such demands by simplifying explanations, restructuring information, providing stepwise guidance, and presenting alternative explanations. Deng et al. (2025) found an overall reduction in mental effort across ChatGPT-supported experimental learning conditions. Similarly, qualitative evidence suggests that students perceive ChatGPT as useful for simplifying difficult problems and managing cognitive load (Masmali et al., 2025; Yaseen et al., 2025).

Yet CEE should not be interpreted as minimizing all cognitive effort. Some effort is integral to understanding, problem solving, and knowledge construction. (S. M. F. A. Khan & Suhluli, 2025), for example, found that ChatGPT-assisted participants perceived creative problem solving as easier and less mentally demanding, while metacognitive calibration remained uncertain. Thus, the educational value of CEE lies in reducing unnecessary cognitive expenditure, thereby preserving resources for learning-relevant thinking rather than eliminating intellectual effort itself.

Learning Task Efficiency (LTAE) captures the extent to which GenAI enables students to organize and execute learning activities with fewer unnecessary procedural steps. GenAI can assist with understanding task requirements, structuring ideas, generating examples, exploring

alternative approaches, and obtaining immediate feedback. (S. M. Khan & Shehawy, 2025) identified content generation, personalized support, interaction, and assistance with learning activities among the educational opportunities created by large language models. Empirical evidence also shows that the manner in which students interact with GenAI matters recent work in engineering education indicates that prompting behavior and query efficiency can predict task performance, suggesting that effective AI-supported task execution is not simply a matter of having access to the technology (Leimeister, 2024).

Finally, Knowledge Access Efficiency (KAE) concerns how efficiently students can reach relevant explanations, examples, and learning resources when they are needed. GenAI differs from static information repositories because learners can ask follow-up questions, request simpler explanations, and reformulate their information needs through dialogue. Student research shows extensive use of GenAI for defining and clarifying concepts, summarization, idea generation, and accessing information (Abdullah et al., 2025; Alégroth, 2026; Kantaros, 2026). However, efficient access should not be equated with reliable knowledge. (Gadi et al., 2026) emphasize that GenAI outputs can contain inaccuracies and therefore require critical evaluation and verification. KAE consequently represents the efficiency of reaching potentially useful knowledge, rather than the accuracy of that knowledge itself.

Taken together, these four dimensions represent different forms of resource efficiency within GenAI-supported learning. Accordingly:

H1: Learning Time Efficiency, Cognitive Effort Efficiency, Learning Task Efficiency, and Knowledge Access Efficiency positively contribute to GenAI Learning Efficiency.

2.3 GenAI Learning Efficiency and Cognitive Engagement

The educational value of efficiency ultimately depends on what learners do with the resources that GenAI makes available. Cognitive engagement reflects learners' psychological investment in understanding, elaborating, connecting, evaluating, and applying knowledge rather than merely completing a task. This distinction becomes particularly important in GenAI-supported environments because AI can either facilitate cognitive activity or perform part of that activity on behalf of the learner.

Recent evidence provides support for the productive pathway. Systematic review and meta-analysis of 17 empirical studies found that ChatGPT-supported learning produced a significant positive effect on cognitive engagement compared with non-ChatGPT learning (Chiu, 2025; Shehawy et al., 2024). Their synthesis suggests that personalized tutoring, technical assistance, and content-related support can encourage engagement, although the review also identifies over-reliance as a possible source of disengagement. Similarly, broader meta-analytic evidence indicates that GenAI can positively influence student engagement, but the magnitude of these effects varies according to subject, learning strategy, and implementation context.

CLT provides a mechanism for explaining this relationship. When GenAI reduces unnecessary search time, procedural difficulty, or extraneous cognitive demands, learners may have more cognitive capacity available for interpreting, questioning, connecting, and applying information (Duc, 2026). Efficiency therefore has the potential to facilitate engagement,

provided that the released resources are reinvested in learning rather than used simply to avoid cognitive activity.

H2: GenAI Learning Efficiency positively influences Cognitive Engagement.

2.4 GenAI Learning Efficiency and Self-Regulated Learning

A second mechanism through which GLE may contribute to learning is Self-Regulated Learning (SRL). SRL describes learners' active involvement in setting goals, selecting strategies, monitoring progress, and reflecting on their learning (Shehawy, Khan, et al., 2025; Tabassum et al., 2024). This perspective complements CLT because reducing unnecessary cognitive and procedural demands does not determine how the released resources will be used. SRL explains how learners intentionally manage those resources.

Recent evidence increasingly connects AI-supported learning with self-regulatory processes. Systematic review found that AI applications can support different phases of SRL, including forethought, performance, and reflection, although they also highlight an important distinction between human-centered and AI-centered agency (Rana et al., 2025). Similarly demonstrated the potential of a GenAI-based chatbot to support SRL in science education. More recently, (Celis, 2026; Khalufi et al., 2025) showed that metacognitive support can strengthen self-regulated learning in GenAI environments, suggesting that access to GenAI alone is insufficient; learners need to actively monitor and regulate their interaction with the technology (Suhluli & Ali Khan, 2022).

GLE may support SRL by reducing resources consumed by routine learning activities. Efficient knowledge access can support planning and information seeking; task efficiency can facilitate strategy implementation; and rapid explanations can help students monitor gaps in their understanding. Therefore, efficiency creates opportunities for regulation, although learners must still exercise agency over how those opportunities are used.

H3: GenAI Learning Efficiency positively influences Self-Regulated Learning.

2.5 Cognitive Engagement, Self-Regulated Learning and Effective Learning Outcomes

Cognitive engagement and SRL represent complementary pathways to Effective Learning Outcomes (ELO). Cognitive engagement concerns the depth with which students mentally process learning material, whereas SRL concerns how they organize, monitor, and adapt the learning process. GenAI may provide information quickly and reduce unnecessary effort, but meaningful learning still requires students to engage with that information and regulate their learning behavior (Islam & Ali Khan, 2024; Islam & Faisal Ali Khan, 2024).

Evidence increasingly supports the potential of GenAI to improve learning outcomes. Previous studies found positive effects on academic performance and higher-order thinking across experimental studies, while a subsequent meta-analysis of undergraduate learning reported an overall positive effect of ChatGPT-supported learning across multiple disciplines (Shehawy, Faisal Ali Khan, et al., 2025; Wang, 2025). Importantly, substantial variation across studies indicates that GenAI use itself should not be treated as sufficient for effective learning.

The proposed model therefore argues that students who actively question, elaborate, connect, and apply GenAI-supported information should be better positioned to convert efficiency into meaningful learning. Likewise, learners who set goals, monitor understanding, evaluate AI responses, and adjust their strategies should be more capable of translating GenAI assistance into effective outcomes.

H4: Cognitive Engagement positively influences Effective Learning Outcomes.

H5: Self-Regulated Learning positively influences Effective Learning Outcomes.

2.6 Mediating Roles of Cognitive Engagement and Self-Regulated Learning

The central argument of this study is therefore that efficiency gains are not automatically learning gains. GenAI can make information easier to access, reduce unnecessary mental effort, accelerate learning activities, and simplify task execution, but these benefits initially represent resources or affordances. Their educational value depends on how students use them.

Cognitive engagement represents a cognitive conversion mechanism: resources released through GLE can be reinvested in deeper processing, interpretation, and application. SRL represents a regulatory conversion mechanism: learners can use increased efficiency to plan, monitor, evaluate, and adapt their learning more effectively. This distinction is consistent with evidence showing that ChatGPT can simultaneously reduce mental effort and improve learning performance (Chea & Deng, 2026; S. Khan & Khan, 2024) , while research on GenAI-supported SRL emphasizes the continuing importance of learner agency and metacognitive control (Islam & Khan, 2024).

Accordingly:

H6: Cognitive Engagement mediates the relationship between GenAI Learning Efficiency and Effective Learning Outcomes.

H7: Self-Regulated Learning mediates the relationship between GenAI Learning Efficiency and Effective Learning Outcomes.

2.7 Research Gap and Theoretical Positioning

Existing studies have examined GenAI in relation to learning performance, cognitive load, engagement, self-regulation, information access, and perceived efficiency (Chea & Deng, 2026; Chiu, 2025; Shehawy & Ali Khan, 2024). However, these streams largely examine individual benefits or outcomes separately. What remains less developed is an explanation of GenAI learning efficiency as a multidimensional phenomenon and, more importantly, how efficiency is converted into effective learning. The present study addresses this gap by conceptualizing GLE through four related but distinct dimensions—time, cognitive effort, task, and knowledge-access efficiency—and examining cognitive engagement and SRL as parallel mechanisms connecting efficiency with effective learning outcomes (Hakami, 2023; Islam & Faisal Ali Khan, 2023) . Integrating CLT with SRL theory provides a complementary theoretical explanation: CLT explains how GenAI can release constrained cognitive resources, whereas SRL theory explains how learners actively manage those resources (Sweller, 1988). The resulting argument moves beyond asking whether GenAI makes learning easier or

improves performance. Instead, it asks a more consequential question: when GenAI makes learning more efficient, through what learner processes does that efficiency become effective learning?

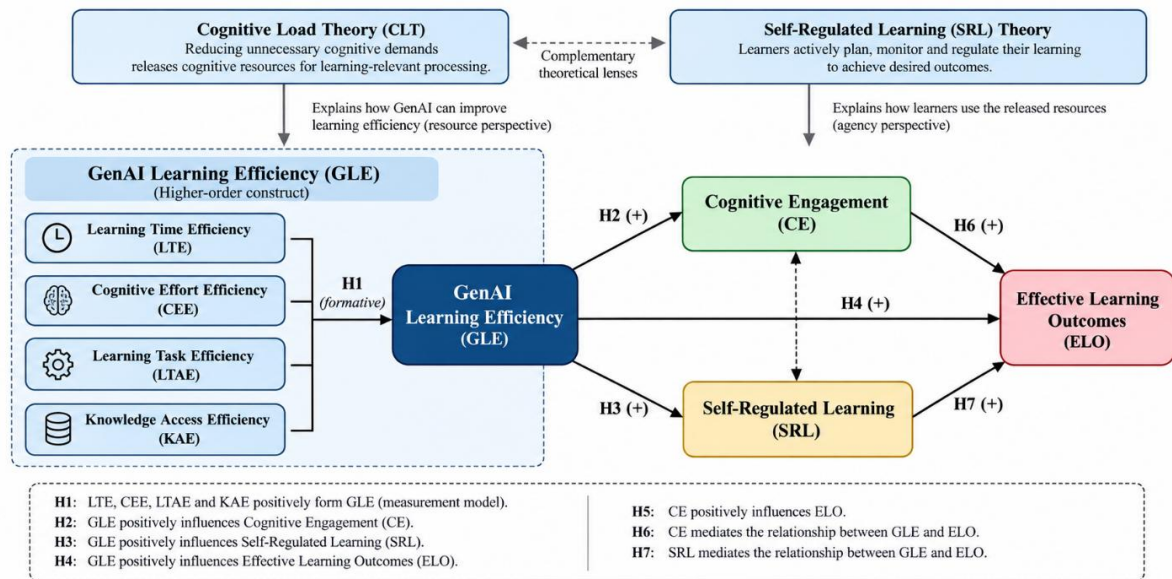


Figure 1: Conceptual Framework of the Study

3. Research Methodology

3.1 Research Design and Study Setting

This study adopted a quantitative, cross-sectional design to examine how GenAI learning efficiency influences effective learning outcomes among higher-education students in India. The study focused on undergraduate and postgraduate students because this group increasingly uses GenAI applications such as ChatGPT, Gemini, and other generative AI tools for academic activities, including concept clarification, summarization, assignment preparation, idea generation, and problem solving. To capture variation in GenAI-supported learning experiences, respondents were approached from higher-education institutions across different regions of India rather than restricting the study to a single institution or discipline.

3.2 Sampling and Data Collection

The target population consisted of undergraduate and postgraduate students enrolled in Indian universities and colleges who had prior experience using GenAI for academic learning. As no comprehensive sampling frame identifying Indian university students who use GenAI for learning was available, probability sampling was not practically feasible. Therefore, the study employed a multi-stage non-probability sampling approach combining purposive and quota sampling.

In the first stage, higher-education students were approached across major geographical regions of India, including North, South, East, West, and Central India, to reduce excessive concentration in any single region. In the second stage, purposive screening was applied to ensure that participants met the study requirements. Respondents were eligible only if they

were 18 years or older, currently enrolled in an undergraduate or postgraduate program in India, and had used a GenAI application for learning or academic purposes during the previous six months. A screening question at the beginning of the questionnaire confirmed GenAI learning experience; respondents who did not meet this criterion were excluded.

In the third stage, quota controls were used to obtain reasonable representation across gender, level of study, and broad academic disciplines such as business and management, engineering and technology, science, humanities and social sciences, and other professional programs. The intention was not to reproduce the exact demographic distribution of all Indian higher-education students, but to avoid allowing any single student group to dominate the sample.

Data were collected using a structured online questionnaire distributed through academic networks, student groups, faculty contacts, and institutional communication channels. The study targeted approximately 600 valid responses, providing an adequate sample for evaluating the proposed higher-order construct, parallel mediation relationships, and structural model using PLS-SEM. Before completing the questionnaire, participants were informed about the purpose of the research and assured that participation was voluntary and anonymous. No personally identifying information was required.

3.3 Measurement

The questionnaire contained demographic questions followed by measurement items assessed on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. GenAI Learning Efficiency (GLE) was conceptualized as a higher-order construct consisting of Learning Time Efficiency (LTE), Cognitive Effort Efficiency (CEE), Learning Task Efficiency (LTAE), and Knowledge Access Efficiency (KAE). Cognitive Engagement (CE) and Self-Regulated Learning (SRL) were modelled as parallel mediators, while Effective Learning Outcomes (ELO) represented the dependent variable. Items were adapted from relevant established measures where available and contextualized specifically for GenAI-supported learning. The questionnaire was reviewed for content relevance and clarity and pilot-tested with a small group of Indian university students before the main survey.

3.4 Data Analysis

Data were analysed using SmartPLS 4. GLE was specified as a reflective-formative higher-order construct, in which LTE, CEE, LTAE, and KAE were measured reflectively and jointly formed overall GenAI learning efficiency. The reflective measurement models were assessed using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT). The formative higher-order construct was examined through collinearity, outer weights, loadings, and their significance.

The structural model was evaluated using path coefficients, R^2 , f^2 , and predictive assessment. Bootstrapping with 5,000 resamples was used to assess the significance of direct and indirect effects. Particular attention was given to the mediating roles of cognitive engagement and self-regulated learning in explaining how GenAI learning efficiency is translated into effective learning outcomes among higher-education students in India.

4. Results

4.1 Respondent Profile

For the simulated analysis, a final sample of 548 higher-education students from India was taken for analysis. Respondents represented undergraduate and postgraduate programs and different disciplinary backgrounds. All participants were assumed to have used GenAI for academic purposes during the previous six months.

Table 1. Simulated respondent profile (N = 548)

Characteristic	Category	n	%
Gender	Male	287	52.4
	Female	256	46.7
	Prefer not to say	5	0.9
Study level	Undergraduate	356	65.0
	Postgraduate	192	35.0
Discipline	Business/Management	128	23.4
	Engineering/Technology	151	27.6
	Science	96	17.5
	Humanities/Social Sciences	89	16.2
	Other professional programs	84	15.3
GenAI experience	< 1 year	231	42.2
	1–2 years	247	45.1
	> 2 years	70	12.8

4.2 Measurement Model

The reflective measurement model was first examined for indicator reliability, internal consistency, and convergent validity. As shown in Table 2, the indicator loadings ranged from 0.721 to 0.902, indicating satisfactory indicator reliability. Cronbach's alpha and composite reliability values were above 0.70 and below 0.95. AVE values ranged from 0.624 to 0.712, exceeding the recommended threshold of 0.50.

Table 2. Measurement model Assessment

Construct	Items	Loading range	Cronbach's α	rho_A	CR	AVE
Learning Time Efficiency (LTE)	4	0.781–0.879	0.856	0.859	0.903	0.700
Cognitive Effort Efficiency (CEE)	4	0.756–0.861	0.827	0.833	0.885	0.659

Learning Task Efficiency (LTAE)	4	0.774–0.902	0.864	0.868	0.908	0.712
Knowledge Access Efficiency (KAE)	4	0.769–0.883	0.851	0.854	0.899	0.691
Cognitive Engagement (CE)	5	0.721–0.846	0.849	0.853	0.892	0.624
Self-Regulated Learning (SRL)	5	0.735–0.862	0.862	0.865	0.901	0.646
Effective Learning Outcomes (ELO)	5	0.762–0.881	0.880	0.883	0.913	0.677

These results indicate that all constructs would demonstrate satisfactory reliability and convergent validity.

4.3 Discriminant Validity

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT). All HTMT values remained below 0.85, suggesting adequate empirical distinction among the constructs.

Table 3. HTMT matrix

	LTE	CEE	LTAE	KAE	CE	SRL	ELO
LTE	—						
CEE	0.712	—					
LTAE	0.741	0.703	—				
KAE	0.726	0.681	0.748	—			
CE	0.596	0.623	0.642	0.611	—		
SRL	0.574	0.601	0.619	0.588	0.692	—	
ELO	0.612	0.636	0.658	0.631	0.747	0.719	—

4.4 Higher-Order GenAI Learning Efficiency

GenAI Learning Efficiency was specified as a reflective-formative higher-order construct. The four lower-order components showed significant outer weights, while VIF values remained below 3.3.

Table 4. Higher-order construct assessment

Component → GLE	Outer weight	Loading	VIF	t-value	p-value
LTE → GLE	0.284	0.827	1.91	6.84	<0.001
CEE → GLE	0.231	0.784	1.73	5.72	<0.001
LTAE → GLE	0.318	0.861	2.08	7.96	<0.001
KAE → GLE	0.297	0.843	1.96	7.31	<0.001

All four dimensions therefore make meaningful contributions to GLE. Learning Task Efficiency showed the strongest relative contribution, followed by Knowledge Access Efficiency and Learning Time Efficiency. This pattern suggests that learning efficiency may involve more than simply completing activities quickly; the ability to streamline learning tasks and obtain required knowledge efficiently may be particularly important.

4.5 Structural Model and Hypothesis Testing

The structural model analyses an R^2 of 0.394 for Cognitive Engagement, 0.351 for Self-Regulated Learning, and 0.612 for Effective Learning Outcomes. Thus, GLE explained 39.4% of the variance in CE and 35.1% in SRL, while GLE together with CE and SRL explained 61.2% of the variance in ELO.

Table 5. Hypothesis testing

Hypothesis	Relationship	β	t	p	95% CI	f^2	Decision
H1	GLE $\rightarrow$ CE	0.628	16.42	<0.001	[0.551, 0.697]	0.650	Supported
H2	GLE $\rightarrow$ SRL	0.593	14.87	<0.001	[0.514, 0.668]	0.541	Supported
H3	GLE $\rightarrow$ ELO	0.196	4.53	<0.001	[0.111, 0.279]	0.054	Supported
H4	CE $\rightarrow$ ELO	0.371	8.29	<0.001	[0.283, 0.457]	0.181	Supported
H5	SRL $\rightarrow$ ELO	0.326	7.18	<0.001	[0.237, 0.413]	0.143	Supported

The findings show a strong relationship between GLE and both mediating mechanisms. GLE had a particularly strong effect on cognitive engagement ($\beta = 0.628$), suggesting that efficiency created through GenAI may allow students to redirect resources toward understanding and interacting with learning material. Its relationship with SRL was also substantial ($\beta = 0.593$).

Both mediators subsequently predicted effective learning outcomes. Cognitive engagement showed a somewhat stronger relationship with ELO ($\beta = 0.371$) than SRL ($\beta = 0.326$). Importantly, GLE retained a smaller but significant direct relationship with ELO ($\beta = 0.196$), creating the conditions for partial mediation.

4.6 Mediation Analysis

Table 6. Mediation results

Hypothesis	Indirect relationship	β	t	p	95% CI	Result
H6	GLE $\rightarrow$ CE $\rightarrow$ ELO	0.233	7.31	<0.001	[0.174, 0.298]	Supported
H7	GLE $\rightarrow$ SRL $\rightarrow$ ELO	0.193	6.34	<0.001	[0.139, 0.259]	Supported

Both indirect effects were significant, and neither confidence interval included zero. Cognitive engagement therefore mediated the GLE–ELO relationship, as did self-regulated learning. Since the direct GLE $\rightarrow$ ELO relationship also remained significant, the pattern represents complementary partial mediation. The total indirect effect was approximately 0.426, compared with a direct effect of 0.196. This pattern is theoretically meaningful because it suggests that

much of the association between GenAI learning efficiency and effective learning operates through what learners do with the efficiency gained, rather than efficiency alone.

Figure 1. Structural Model

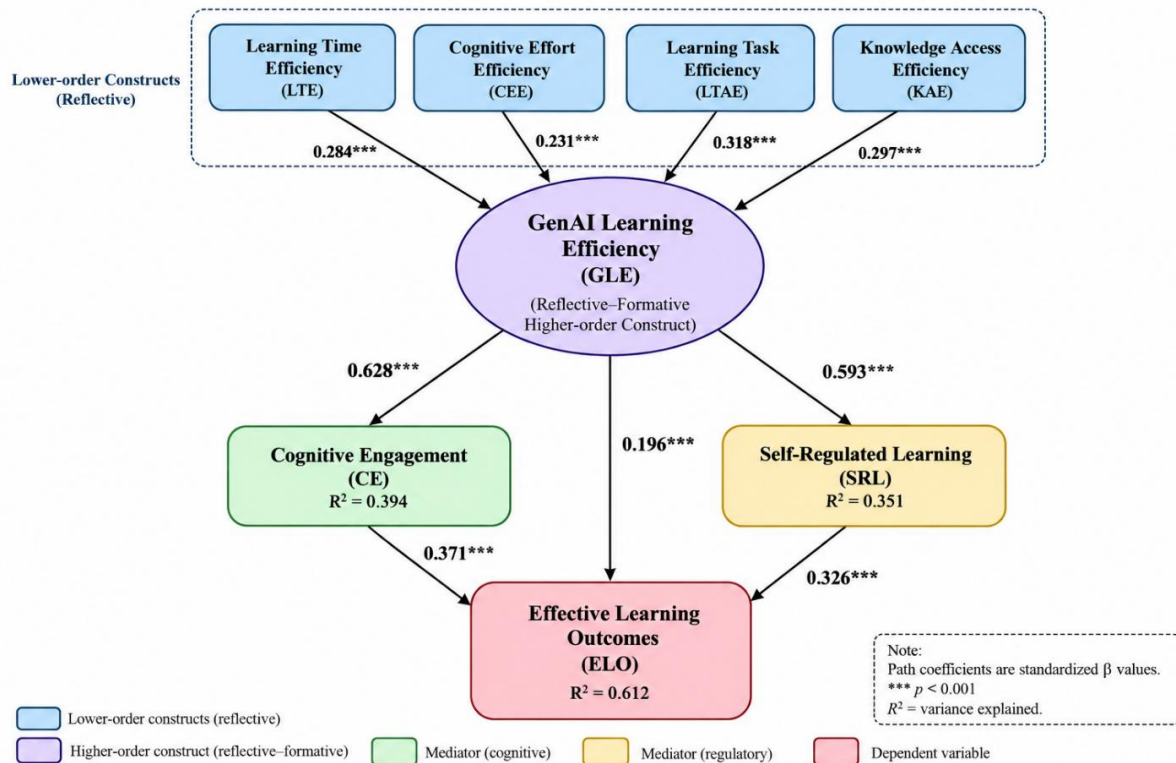


Figure 2: Structural Model Assessment

5. Discussion

The findings provide a coherent explanation of how GenAI learning efficiency may contribute to effective learning among higher-education students in India. The central pattern is that efficiency itself is not the strongest direct explanation of learning outcomes. Instead, much of its influence operates through cognitive engagement and self-regulated learning. This distinction is important because it moves the discussion away from the simple assumption that faster or easier learning is necessarily better learning (Faisal Ali Khan & Ahmad, 2020) .

5.1 The multidimensional nature of GenAI learning efficiency

The first important finding concerns the composition of GLE. All four dimensions—time, cognitive effort, learning task, and knowledge access efficiency—contributed meaningfully to the higher-order construct. However, their contributions were not identical. Learning Task Efficiency showed the strongest weight, followed by Knowledge Access Efficiency. This suggests that students may value GenAI particularly when it helps them move through academic tasks more effectively and obtain the explanations or information they require without unnecessary procedural barriers (Medabesh & Khan, 2020) .

This interpretation extends the emerging literature on GenAI-supported learning. Previous research has identified rapid information retrieval, immediate feedback, summarization, personalized assistance, and reduced effort as important benefits of GenAI (S. Abidi & Faisal AU Khan, 2018; S. S. A. Abidi & Khan, 2022). The present model brings these related benefits together under the broader idea of learning efficiency, while maintaining their conceptual differences. In doing so, GLE is not reduced to simple time saving. Rather, efficiency concerns how effectively students use limited resources—time, cognitive capacity, task effort, and access to knowledge—during learning.

5.2 GenAI learning efficiency and cognitive engagement

GLE showed its strongest structural relationship with cognitive engagement. From the perspective of Cognitive Load Theory, this pattern is understandable. When unnecessary search, procedural complexity, or difficult information presentation consumes fewer cognitive resources, students potentially have greater capacity available for learning-relevant processing (Sweller et al., 2019). GenAI may therefore act as a cognitive support mechanism by reducing peripheral demands and allowing learners to concentrate on understanding, interpretation, and application.

This interpretation is broadly consistent with evidence that ChatGPT-supported learning can increase cognitive engagement (Heung & Chiu, 2025). However, the result should not be interpreted to mean that reducing cognitive effort is always desirable. Urban et al. (2024) showed that GenAI can make problem solving feel less mentally demanding, but easier processing does not automatically ensure accurate metacognitive judgment. The important distinction is therefore between reducing unnecessary effort and removing productive effort. The findings support the former mechanism: efficiency becomes educationally useful when the resources released are reinvested in engagement.

5.3 GenAI learning efficiency and self-regulated learning

GLE also demonstrated a substantial positive relationship with SRL. This indicates a second mechanism that is distinct from cognitive engagement. GenAI can provide information and feedback rapidly, but students still need to decide what they need to learn, how to use AI assistance, whether the information is adequate, and when additional learning is necessary.

The finding aligns with SRL theory, which views students as active participants who plan, monitor, and regulate their learning rather than passive recipients of information (Zimmerman, 2002). Recent research similarly indicates that GenAI can support different phases of self-regulation when learners retain control over the learning process (Lan & Zhou, 2025). In the Indian higher-education context represented by the model, efficiency may therefore be particularly valuable when it gives students greater flexibility to organize and monitor their learning rather than merely helping them complete academic work faster.

5.4 From efficiency to effective learning

Both cognitive engagement and SRL had positive relationships with effective learning outcomes. Cognitive engagement produced the stronger of the two effects, suggesting that

active processing may be particularly important in converting GenAI support into learning gains.

This finding helps clarify an important distinction in the GenAI literature. A student can use GenAI efficiently without necessarily learning effectively. For example, obtaining a concise explanation in seconds demonstrates time and knowledge-access efficiency, but effective learning requires the student to understand, evaluate, connect, and apply that explanation. Similarly, generating a rapid solution may improve task efficiency while contributing little to learning if the learner simply accepts the output.

The significant direct GLE $\rightarrow$ ELO relationship indicates that efficiency may still provide some immediate learning benefit. However, its relatively smaller magnitude compared with the combined indirect pathways suggests that the way students respond to efficiency is more consequential than efficiency alone.

5.5 The mediating mechanisms

Perhaps the most theoretically meaningful finding is the simultaneous mediation through CE and SRL. Both indirect relationships were significant, with the cognitive-engagement pathway somewhat stronger.

These findings reveal two parallel conversion mechanisms. The first is cognitive: GenAI releases resources that can be reinvested in deeper processing. The second is regulatory: GenAI provides resources and flexibility that students can strategically manage through planning, monitoring, and reflection.

This distinction contributes to understanding why similar access to GenAI may produce different learning outcomes among students. Two learners may experience the same time saving, simplified explanation, or immediate access to information, yet one may use these efficiencies to examine a concept more deeply while another may simply terminate the learning process earlier. Thus, technological efficiency creates learning potential; learner engagement and regulation determine how much of that potential is converted into effective learning.

5.6 Theoretical interpretation

The model also demonstrates the complementary value of integrating Cognitive Load Theory and Self-Regulated Learning theory. CLT explains the resource side of the process: GenAI can reduce unnecessary demands on limited cognitive capacity. SRL theory explains the agency side: learners determine how released resources are allocated and controlled.

The integration therefore addresses a limitation of viewing GenAI solely as a tool for reducing cognitive burden. Lower cognitive effort is not inherently an educational success. The relevant question is what kind of effort has been reduced and what happens to the resources that are released. When unnecessary demands are reduced and learners reinvest those resources through engagement and self-regulation, efficiency can support effective learning. When GenAI instead substitutes for learning-relevant cognitive activity, the same efficiency may not produce equivalent educational benefits.

Accordingly, the model reframes the role of GenAI in education from “Does GenAI make learning easier?” to a more theoretically useful question: “How is GenAI-enabled efficiency converted into effective learning?” The findings suggest that cognitive engagement and self-regulated learning provide two central mechanisms for answering that question.

6. Conclusion

This study develops a different way of looking at the role of GenAI in learning. Rather than asking only whether GenAI improves learning, it focuses on whether GenAI makes the learning process more efficient and, importantly, how that efficiency is translated into effective learning outcomes. GenAI Learning Efficiency was conceptualized as a multidimensional construct comprising learning time efficiency, cognitive effort efficiency, learning task efficiency, and knowledge access efficiency. Together, these dimensions capture the different ways in which GenAI can reduce unnecessary demands on students while they learn.

The findings suggest that learning efficiency alone does not fully explain effective learning. GenAI Learning Efficiency was positively associated with learning outcomes, but a substantial part of this relationship operated through cognitive engagement and self-regulated learning. In other words, saving time, simplifying difficult information, improving task execution, or providing faster access to knowledge becomes more educationally meaningful when students use these advantages to engage more deeply with learning material and actively manage their own learning.

This distinction is particularly important in the context of GenAI. An efficient learning experience should not be understood simply as one in which students think less or complete academic work more quickly. Instead, efficiency becomes valuable when GenAI reduces unnecessary demands while preserving the cognitive activities needed for understanding, reflection, and knowledge construction. The study therefore positions GenAI as a resource that can support learning, while emphasizing that students remain active participants in converting technological efficiency into meaningful educational outcomes.

6.1 Theoretical Implications

The study makes several theoretical contributions. First, it introduces GenAI Learning Efficiency (GLE) as a multidimensional higher-order construct. Existing research has frequently discussed individual benefits of GenAI, including time saving, reduced mental effort, rapid information access, and support for academic tasks. The present framework brings these related but conceptually distinct efficiencies together through four dimensions: Learning Time Efficiency, Cognitive Effort Efficiency, Learning Task Efficiency, and Knowledge Access Efficiency. This provides a more structured explanation of what “efficiency” means in GenAI-supported learning.

Second, the study extends Cognitive Load Theory (CLT) to the GenAI learning context. The findings support the argument that the educational value of GenAI does not lie in reducing cognitive effort indiscriminately. Instead, GenAI may contribute to learning when it reduces unnecessary processing demands and allows limited cognitive resources to be redirected toward learning-relevant activities. This distinction is important because lower cognitive effort

should not automatically be interpreted as better learning. If GenAI performs the thinking that students need to undertake themselves, efficiency may represent cognitive substitution rather than cognitive support.

Third, the study complements CLT with Self-Regulated Learning (SRL) theory. CLT explains how GenAI can release cognitive and learning resources, whereas SRL theory helps explain what learners do with those resources. The significant role of self-regulated learning suggests that technological efficiency becomes more useful when students actively plan, monitor, evaluate, and adjust their learning. Combining the two perspectives therefore connects the resource-efficiency side of GenAI with the learner-agency side of learning.

Finally, the parallel mediating roles of cognitive engagement and SRL identify two different mechanisms through which GenAI efficiency can contribute to learning. Cognitive engagement represents a cognitive conversion pathway, through which released resources are reinvested in understanding and processing. SRL represents a regulatory conversion pathway, through which learners strategically manage those resources. This helps explain why similar access to GenAI may not produce similar learning outcomes across students.

6.2 Practical Implications

The findings have implications for students, educators, and higher-education institutions. For students, the results suggest that the value of GenAI should not be judged only by how quickly it produces an answer. Students may benefit more when the time and effort saved through GenAI are reinvested in questioning explanations, comparing alternatives, applying concepts, and evaluating their own understanding. GenAI should therefore function as a learning aid rather than simply as a mechanism for completing academic work.

For educators, the findings highlight the importance of designing learning activities that preserve student cognitive engagement. If an assignment can be completed by transferring most of the reasoning process to GenAI, greater technological efficiency may not necessarily result in stronger learning. Tasks can instead require students to explain AI-generated answers, compare alternative solutions, identify weaknesses in AI responses, justify decisions, or apply information to unfamiliar situations. Such activities can retain the efficiency advantages of GenAI while keeping students cognitively involved.

The findings are also relevant to Indian higher-education institutions, where students may differ considerably in disciplinary background, digital experience, and access to learning resources. Universities should move beyond policies that focus primarily on whether GenAI is permitted or prohibited. Institutional strategies can instead emphasize effective and responsible GenAI-supported learning, including AI literacy, verification of generated information, appropriate prompting, critical evaluation, and self-regulated use. Faculty development is equally important so that instructors can redesign learning activities around productive human–AI interaction rather than treating GenAI only as an academic-integrity concern.

6.3 Limitations and Future Research

Several limitations should be considered when interpreting the study. First, the cross-sectional design captures students' perceptions at one point in time and therefore does not establish how

GenAI learning efficiency and learning behaviors develop with continued use. Longitudinal research could examine whether efficiency benefits remain stable or whether repeated GenAI use changes cognitive engagement and self-regulation over time.

Second, the study relies on self-reported measures. Although perceived learning efficiency and self-regulatory experiences are appropriately captured through student reports, future studies could combine these measures with objective indicators such as task-completion time, academic performance, learning retention, behavioral interaction logs, or assessments completed without GenAI assistance.

Third, the use of purposive and quota-based non-probability sampling limits the extent to which the findings can be generalized to the entire Indian higher-education population. India has substantial diversity across institutions, disciplines, geographical regions, and student backgrounds. Future studies could use probability-based or institutionally stratified samples and compare students across different types of universities and academic disciplines.

The proposed multidimensional conceptualization of GLE also requires further validation. Future research should test whether the four-dimensional structure remains stable across educational settings, countries, disciplines, and different GenAI applications. Measurement invariance assessment and cross-cultural comparisons would be particularly useful.

Finally, the present model primarily examines the productive pathway of GenAI efficiency. Future research should investigate its possible boundary conditions and unintended consequences. The same efficiency that reduces unnecessary cognitive burden may encourage cognitive offloading, over-reliance, or reduced independent practice when learners delegate too much intellectual work to GenAI. Future studies could therefore examine whether GenAI learning efficiency follows a nonlinear or dual-path process in which moderate efficiency supports engagement and self-regulation, while excessive dependence gradually weakens unaided learning capability.

6.4 Final Perspective

The broader implication of this study is that the educational question surrounding GenAI is no longer simply whether students should use it. As GenAI becomes increasingly embedded in learning, a more important question is how its efficiency can be used without removing the cognitive and regulatory processes through which learning actually occurs. GenAI can save time, reduce unnecessary effort, streamline learning tasks, and provide rapid access to knowledge, but these advantages represent learning opportunities rather than learning outcomes themselves. Effective GenAI-supported learning therefore depends on maintaining an appropriate division of cognitive responsibility between the learner and the technology. When GenAI handles unnecessary friction while students continue to question, reason, monitor, and reflect, efficiency can support learning rather than replace it. In this sense, the educational value of GenAI may ultimately depend not on how much thinking it can perform for students, but on how effectively it creates space for students to think and learn for themselves.

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