Explaining Competence Development in AI-Enabled Learning Environments: A Stimulus-Organism-Response Model for Higher Education

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Abstract: Artificial intelligence (AI) is rapidly reshaping higher education, yet existing research remains more effective at describing technological functions and structural changes than at explaining how AI-enabled learning environments influence learner development. To address this gap, this conceptual study develops a theoretical framework based on the Stimulus-Organism-Response (S-O-R) model. Within this framework, AI-enabled learning environments are conceptualized as contextual stimuli, learners' behavioral and psychological engagement as organism variables, and competence development as the response. Drawing on research in AI-enabled learning, interdisciplinary education, learning analytics, and generative AI, the framework identifies three dimensions of contextual stimuli—physical context, social interaction, and intelligent systems—and argues that these conditions shape competence development through the reciprocal dynamics of behavioral and psychological engagement. The study addresses this gap by offering a mechanism-oriented explanation of AI-enabled learning, integrating process-optimization and structural-transformation perspectives, and reconceptualizing learning outcomes from narrow performance indicators to broader competence development. It further argues that the educational effects of AI are conditional rather than uniformly beneficial. By clarifying the pathway from AI-enabled learning environments to competence development, the study provides a theoretical foundation for future empirical research in higher education.

Keywords: Artificial Intelligence; AI-Enabled Learning Environments; Higher Education; Competence Development; Stimulus-Organism-Response; Learner Engagement

1. Introduction

Artificial intelligence (AI) is increasingly reshaping the organization and practices of higher education and the conditions under which teaching and learning take place. From intelligent tutoring systems and learning analytics platforms to generative AI technologies represented by large language models, AI has become progressively embedded in course design, learning support, and assessment processes [1]. In universities worldwide, these technologies are adopted not only to improve instructional efficiency but also to support more personalized learning, collaborative inquiry, and the development of higher-order competencies.

These developments are particularly visible in interdisciplinary and STEM education. Through intelligent feedback systems, adaptive learning platforms, and AI-mediated interaction environments, learning activities can now be organized in more flexible, responsive, and data-informed ways. As a result, AI-enabled teaching is increasingly regarded as an important driver of digital transformation in higher education.

Yet the rapid expansion of AI applications has not been matched by equally clear theoretical explanations of how AI-enabled learning environments facilitate learning transformation. Existing scholarship has generated valuable insights into the educational role of AI, but these insights have tended to develop along two broad lines. One line emphasizes process optimization, treating AI primarily as a technological means of improving learning efficiency and supporting instructional processes. The other highlights structural transformation, focusing on how AI reshapes learning environments, pedagogical design, and even the organization of knowledge work.

Both perspectives are important, but neither fully explains how AI-enabled learning environments

influence learner development through internal engagement processes. Research grounded in process optimization tends to foreground technological efficiency, feedback, and performance improvement. Research informed by structural transformation broadens the discussion to changes in educational organization and learning ecology but often leaves the learner-level mechanism underdeveloped. Consequently, the question of how AI-enabled learning environments shape behavioral engagement and psychological engagement—and how these, in turn, contribute to competence development—remains insufficiently theorized.

This gap becomes even more significant in light of emerging concerns about the unintended consequences of AI in education. While AI-supported systems can improve task efficiency and provide timely instructional support, some scholars have cautioned that uncritical or excessive reliance on AI tools may reduce opportunities for independent inquiry and critical reflection if used without appropriate pedagogical guidance. In addition, algorithm-driven personalization may risk reinforcing existing ability differences if learning tasks are differentiated in ways that limit learners' exposure to complex problem-solving activities. More broadly, recent discussions of generative AI have highlighted potential tensions between technological assistance and the development of creativity and critical thinking [2,3]. These tensions suggest that it is no longer sufficient to discuss AI solely in terms of technological functionality; what is needed is a clearer account of the mechanisms through which AI-enabled learning environments influence learning processes and outcomes.

To address this issue, this conceptual study develops a theoretical framework based on the Stimulus-Organism-Response (S-O-R) model to explain how AI-enabled learning environments facilitate learning transformation in higher education. Within this framework, AI-enabled learning environments are conceptualized as contextual stimuli, learners' behavioral engagement and psychological engagement as organism variables, and learning outcomes as competence development.

This study makes three contributions to the literature. First, it develops a mechanism-oriented framework explaining how AI-enabled learning environments influence learning transformation through learners' behavioral and psychological engagement. Second, it integrates two dominant perspectives in the AI-in-education literature—process optimization and structural transformation—within a unified analytical framework. Third, it reconceptualizes learning outcomes in AI-enabled educational contexts from performance improvement to competence development, with particular attention to problem solving, interdisciplinary integration, and self-regulated learning.

2. Literature Review

2.1 Two Perspectives on AI-Enabled Higher Education

Research on AI applications in higher education has expanded rapidly over the past decade. Systematic reviews show that AI in education has evolved from early applications such as intelligent tutoring systems and automated grading to more advanced forms including learning analytics, adaptive learning systems, and generative AI-based support [1]. In interdisciplinary and STEM education in particular, AI-enabled teaching has become an increasingly visible area of inquiry as AI-supported instructional practices have become more diverse and pedagogically integrated.

One influential strand of this literature adopts what can be termed a process-optimization perspective. From this viewpoint, AI is primarily understood as a tool for improving the efficiency and quality of learning processes. Research in this tradition focuses on how AI analyzes learner behavior, monitors progress, and provides feedback that supports more adaptive forms of instruction. Xing et al. (2021) [4], for example, used Bayesian network modeling to assess engineering design processes by linking learners' behavioral trajectories to competence structures. Lee et al. [5] similarly showed that AI-supported systems can identify critical points in the learning process and support targeted intervention in interdisciplinary tasks. Related studies suggest that AI-based tools can also support collaborative problem solving and self-regulated learning. For instance, Iku-Silan et al. [6] found that decision-guiding chatbots can scaffold interdisciplinary cognition through dynamic guidance, while García-Senín et al. [7] showed that learning analytics systems can strengthen self-regulation by providing continuous, data-informed feedback.

This body of work demonstrates that AI can make learning processes more visible, adaptive, and potentially more effective. At the same time, its explanatory logic remains closely tied to optimization. Learners are often represented through behavioral traces captured in learning data, while educational value is frequently inferred from improved prediction, faster intervention, or better performance. Less attention has been paid to how such process-level support is experienced by learners within broader learning environments and how it contributes to longer-term developmental outcomes.

A second strand of research adopts a structural-transformation perspective. Rather than focusing on localized improvements in instructional processes, this perspective emphasizes how AI reshapes the broader conditions of teaching and learning. AI is therefore understood not simply as an instructional tool but as part of a wider transformation in learning environments, pedagogical design, and knowledge production. Yannier et al. [8], for instance, demonstrated that mixed-reality systems can create immersive contexts that support active and experiential learning in STEM education. Dong et al. [9] similarly showed that child-robot musical theatre can integrate arts and engineering in ways that reorganize interdisciplinary learning experiences. Chaipidech et al. [10] further showed that teacher professional development programs grounded in the TPACK framework can support interdisciplinary STEM instruction. Likewise, Toivonen et al. [11] found that co-designing machine learning applications with students can broaden opportunities for participation and deepen engagement with computational concepts. Compared with the process-optimization perspective, this second strand is better suited to explaining how AI changes the educational environment itself—how learning tasks are structured, how teachers are supported, and how learning spaces are organized. It is therefore particularly useful for understanding AI as part of broader transformations in educational structures and learning ecologies. However, this perspective also has limitations. Much of the discussion remains focused on systems, environments, and pedagogical arrangements, while the learner-level mechanisms through which these changes influence development are often left implicit.

Taken together, these perspectives capture important dimensions of AI-enabled education but also reveal a key limitation in the current literature. Research has become increasingly effective at identifying what AI changes in learning processes and educational structures, yet it remains less clear how these changes translate into learning transformation. What is still needed is a clearer account of the mechanisms through which AI-enabled learning environments shape learner development. Although several cited studies were conducted in K-12 or teacher development contexts, they are included here because they illustrate mechanisms of AI-mediated scaffolding, participation, and environmental restructuring that are theoretically relevant to higher education learning environments.

2.2 The Separation of Behavioral and Psychological Mechanisms

Another limitation in the literature lies in the tendency to treat behavioral and psychological mechanisms as separate analytical domains. This separation fragments the process through which AI-enabled environments influence learning outcomes.

On the behavioral side, many studies focus on observable indicators such as participation, interaction patterns, and task persistence. Xing et al. [4], modeled engineering design processes using learner behavioral data while Lee et al. [5] examined behavioral indicators of learning dynamics in AI-supported interdisciplinary tasks. Santana et al. [12] also showed that interactive learning models can transform classroom activity into a dynamic inquiry process in which students construct knowledge through repeated experimentation and observation. These studies are valuable because they make learner engagement empirically traceable. However, they often explain learning primarily in terms of observable activity, without addressing how learners interpret or regulate the AI-supported contexts in which those behaviors occur.

On the psychological side, other studies examine learners' motivational and affective states, including self-efficacy, anxiety, satisfaction, and perceived cognitive challenge. Hsu et al. [13] found that an educational robot-based interdisciplinary activity reduced target-language learning anxiety while strengthening cooperation-related social skills. Iku-Silan et al. [6] similarly reported that AI-supported interaction can enhance learners' satisfaction and

team efficacy in collaborative tasks. These studies show that AI-enabled environments influence how learners feel, evaluate their own competence, and sustain engagement. However, research in this area often pays less attention to the environmental structures through which these psychological states are shaped.

In this study, psychological engagement is used as an umbrella concept referring to learners' motivational, affective, and cognitively appraised states that shape how they experience and sustain participation in AI-enabled learning.

The problem, therefore, is not simply that behavior and psychology are studied separately, but that this separation weakens the explanatory chain linking environmental conditions, engagement processes, and learning outcomes. Behavioral studies risk reducing learning to measurable traces, whereas psychological studies may abstract internal states from the contexts in which they arise. As a result, existing research often explains either what learners do or how they feel, but rarely how AI-enabled learning environments shape both dimensions simultaneously.

Recent studies on generative AI reinforce this point. Evidence suggests that AI-supported learning can influence both cognitive outcomes—such as critical thinking and problem-solving—and non-cognitive outcomes including motivation and self-efficacy [14-17]. This indicates that the educational effects of AI cannot be adequately understood through behavioral or psychological variables alone; instead, these dimensions should be treated as interconnected components of a broader engagement mechanism.

This limitation becomes even more apparent when considering the dual character of AI in education. On the one hand, research suggests that AI can enhance motivation, emotional engagement, academic performance, and higher-order thinking by enabling real-time regulation, collaborative support, and immersive learning experiences. On the other hand, the literature also highlights risks such as learning dependency, weakened autonomous inquiry, and the reinforcement of ability differences through algorithm-driven task differentiation. Moreover, some scholars have cautioned that excessive reliance on generative AI may undermine creativity and critical thinking [2,3]. These tensions cannot be fully understood if behavioral and psychological effects are examined separately rather than as interconnected elements of a broader engagement mechanism.

What remains underdeveloped, therefore, is an integrated theoretical perspective explaining how AI-enabled learning environments function as contextual stimuli, how these stimuli shape learners' behavioral and psychological engagement, and how these processes jointly contribute to learning transformation.

2.3 Research Gap: Toward Mechanism Integration

The foregoing review suggests that the literature on AI-enabled higher education has generated important insights but still exhibits two major limitations. First, much of the existing work focuses either on technological functionality or on structural transformation while offering limited explanation of the mechanisms through which AI-enabled learning environments influence learning transformation. Second, behavioral and psychological engagement are often treated as separate outcomes rather than as interdependent processes through which environmental conditions shape learner development.

These limitations point to the need for a more integrated analytical framework. Such a framework should not only describe the educational value of AI or the structural changes it introduces; it should also explain how AI-enabled learning environments operate as contextual conditions that shape learners' engagement and, through that engagement, contribute to competence development.

To address this gap, the present study adopts the Stimulus-Organism-Response (S-O-R) framework as its theoretical foundation. By conceptualizing AI-enabled learning environments as environmental stimuli, learners' behavioral and psychological engagement as organism variables, and competence development as the response, the study aims to provide a mechanism-based explanation of learning transformation in AI-enabled higher education.

3. Theoretical Model

3.1 Theoretical Foundation: The Stimulus-Organism-Response Framework

As the preceding review has shown, what remains insufficiently explained in the literature is not whether AI changes educational

environments, but how such changes translate into learner development. Existing studies show that AI can optimize learning processes and reshape instructional structures, yet they often stop short of explaining how these changes are internalized by learners and translated into developmental outcomes. This explanatory gap makes the Stimulus-Organism-Response (S-O-R) framework particularly relevant to the present study.

Originally proposed by Mehrabian and Russell (1974) [18], the S-O-R framework explains how environmental stimuli influence behavior and outcomes through individuals' cognitive and affective states. Rather than assuming a direct link between external conditions and observable outcomes, the model emphasizes that environmental factors are processed through organismic states—such as cognition, affect, and motivation—before shaping behavioral or developmental responses. In this sense, the framework is particularly useful when the key issue is not merely environmental change, but how such change becomes meaningful at the level of the learner.

The framework has since been applied across several fields, including consumer behavior, information systems, and organizational studies, to explain how technology-rich environments influence human action through psychological processes [19]. Its value lies in integrating environmental conditions, engagement processes, and outcomes within a single explanatory structure. This integrative capacity is especially relevant in AI-enabled educational contexts, where learning environments increasingly consist of interconnected configurations of technologies, interactions, and data-driven support systems rather than single tools or platforms.

In this study, the S-O-R framework is adopted as a mechanism-based lens for explaining learning transformation in AI-enabled higher education. Within this framework, AI-enabled learning environments are conceptualized as environmental stimuli (S), learners' behavioral and psychological engagement as organism variables (O), and learning outcomes as competence development (R).
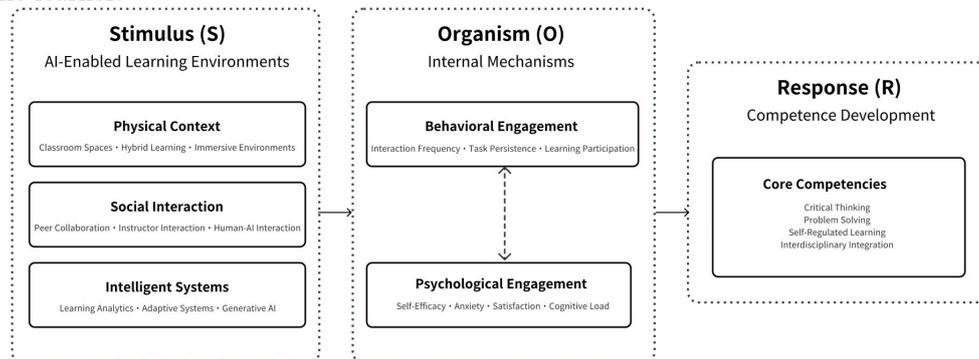

Figure 1. AI-Enabled Learning Mechanism Model Based on the S-O-R Framework.

Based on this theoretical logic, the present study proposes an AI-enabled learning mechanism model grounded in the S-O-R framework (see Figure 1). The model explains how AI-enabled learning environments influence competence development through the mediating processes of behavioral and psychological engagement.

In short, the S-O-R framework highlights an explanatory chain that remains underdeveloped in AI-in-education research: how AI-enabled learning environments shape learner engagement and how such engagement contributes to competence development.

3.2 Stimulus (S): AI-Enabled Learning Environments

Within the S-O-R framework, stimuli refer to environmental conditions that influence individuals' internal states and subsequent responses. In AI-enabled education, however, the stimulus cannot be understood as a single technological artifact. What matters is not merely the presence of AI but the broader learning environment in which it is embedded. For this reason, the present study conceptualizes AI-enabled learning environments as multidimensional contextual stimuli rather than isolated tools or systems.

As illustrated in Figure 1, the stimulus component of the model represents AI-enabled learning environments as a structured configuration of contextual conditions. Drawing on the literature reviewed earlier, these stimuli are organized into three interrelated dimensions: physical context, social interaction, and

intelligent systems. This categorization provides an analytic heuristic for understanding how different layers of AI-enabled environments shape learner engagement, highlighting the material conditions of learning, the structure of participation, and the technological logic of adaptive support.

The first dimension, physical context, refers to the spatial and infrastructural conditions through which learning activities are organized. In AI-enabled settings, learning environments increasingly extend beyond the traditional classroom to include digitally augmented spaces, hybrid learning environments, and immersive learning arrangements. Yannier et al. [8], for example, showed that mixed-reality systems can combine physical and digital spaces to support active exploration and experiential learning. Such environments influence how learners perceive tasks, access information, and engage with complex problems.

The second dimension, social interaction, refers to the relational structure through which learning occurs. This includes interactions among students, teachers, and AI-mediated agents. In AI-enabled environments, interaction often takes place within hybrid participation structures in which AI systems provide guidance, feedback, and scaffolding. Iku-Silan et al. [6] demonstrated that decision-guiding chatbots can support interdisciplinary problem solving by shaping team interaction and cognitive integration. AI-supported participation can therefore broaden opportunities for engagement and collaborative knowledge construction.

The third dimension, intelligent systems, refers to AI-driven technologies that process learner data, generate feedback, and support adaptive learning. These include learning analytics platforms, adaptive learning systems, and generative AI tools. Unlike static technologies, intelligent systems operate through continuous monitoring, interpretation, and response. García-Senín et al. [7] showed that learning analytics systems can support self-regulated learning by helping learners track progress and adjust strategies. As a result, intelligent systems make learning environments more responsive, personalized, and capable of timely intervention. Together, these three dimensions form the contextual stimulus structure of AI-enabled learning environments. Their significance lies in configuring the material, relational, and technological conditions under which learners engage.

3.3 Organism (O): Behavioral and Psychological Engagement

In the S-O-R framework, the organism refers to the internal processes through which environmental stimuli are translated into outcomes. In AI-enabled learning contexts, this level is particularly important because the impact of AI does not follow automatically from technological presence. Instead, it depends on how learners engage with the learning environment. Accordingly, the present study conceptualizes organism variables as behavioral engagement and psychological engagement.

As shown in Figure 1, these two forms of engagement constitute the internal mechanism through which contextual stimuli influence learning outcomes.

Behavioral engagement refers to learners' observable participation in learning activities, including interaction frequency, task persistence, and sustained involvement in problem-solving processes. AI-supported systems can shape these behaviors by identifying critical points in learning processes, providing feedback, and scaffolding task progression. Xing et al. [4] showed that behavioral modeling can reveal process patterns in engineering design tasks, while Lee et al. (2023) [5] demonstrated that AI-supported systems can detect critical learning points and enable timely intervention. Behavioral engagement therefore reflects the observable dimension of learners' interaction with AI-enabled learning environments.

Psychological engagement refers to learners' motivational and affective states, including self-efficacy, anxiety, satisfaction, and cognitive load. AI-supported tools may influence these states by providing personalized feedback, reducing uncertainty, and supporting sustained task involvement. Hsu et al. [13] found that educational robots could reduce language-learning anxiety while supporting collaborative learning skills. Iku-Silan et al. [6] similarly reported that AI-mediated support can enhance learner satisfaction and team efficacy. Recent studies on generative AI further suggest that AI-supported learning can strengthen critical thinking, problem-solving ability, motivation, and self-efficacy under appropriate instructional conditions [14-17].

Importantly, behavioral and psychological engagement should not be treated as independent

outcomes. Instead, they operate as mutually reinforcing processes. Positive psychological states may increase persistence and participation, while sustained behavioral involvement can strengthen confidence and deepen engagement. Together, these dimensions form the mechanism through which contextual stimuli become educationally meaningful.

By conceptualizing engagement in this integrated way, the present model addresses a limitation identified in previous research, which often examines behavioral indicators or psychological states in isolation. Treating them as interconnected dimensions provides a more complete explanation of how AI-enabled learning environments influence learner development.

3.4 Response (R): Competence Development

In much educational research, learning outcomes are measured in terms of academic performance, such as grades or test scores. Although such indicators are useful, they are often too narrow to capture learning in AI-enabled interdisciplinary environments. When learners engage in complex, collaborative, and technology-mediated tasks, the educational value of these experiences cannot be fully understood through performance metrics alone. For this reason, the response variable in the present study is conceptualized as competence development rather than performance improvement.

Competence development refers to relatively durable and transferable capacities that enable learners to solve complex problems, integrate knowledge across domains, and regulate their own learning in unfamiliar contexts. Unlike performance indicators, which capture immediate learning outcomes, competence development reflects longer-term capabilities built through engagement in complex educational environments.

As illustrated in Figure 1, competence development represents the response dimension of the S-O-R mechanism model.

In AI-enabled contexts, these capacities may include problem-solving ability, interdisciplinary integration, and self-regulated learning. Such outcomes are particularly relevant because AI-enabled learning environments often involve authentic tasks, adaptive feedback, and collaborative inquiry. García-Senín et al. [7] showed that learning analytics systems can support self-regulated learning by helping learners monitor and adjust their progress. These findings further suggest that generative AI may contribute to higher-order cognitive development, particularly in terms of critical thinking and problem-solving.

Conceptualizing response in terms of competence development also aligns with broader developments in higher education. Universities are increasingly expected not only to improve academic performance but also to cultivate learners who can think critically, address unfamiliar problems, and regulate their own learning.

3.5 Mechanism Pathway of the S-O-R Model

The theoretical model developed in this study can be summarized as the following mechanism pathway: AI-enabled learning environments (S) → Behavioral and psychological engagement (O) → Competence development (R).

Figure 1 visually summarizes this mechanism pathway and illustrates how contextual stimuli, learner engagement, and competence development are conceptually connected within the S-O-R framework.

This pathway suggests that AI-enabled learning environments influence learner development not directly, but through the processes by which learners engage with those environments. In other words, the significance of AI lies not only in what it adds to learning environments, but in how it reshapes the conditions under which learners participate, interpret tasks, and persist.

At the stimulus level, AI-enabled learning environments provide structured configurations of physical, relational, and technological conditions. These elements do not automatically generate educational outcomes. Rather, they become meaningful when they shape learner engagement. At the organism level, this engagement takes behavioral and psychological form as learners participate in activities, persist in tasks, interact with others, and evaluate their own competence. Through these processes, environmental change is translated into developmental outcomes.

This mechanism pathway also integrates the two perspectives identified in the literature review. The process-optimization perspective is reflected in how AI-supported systems influence participation, feedback, and learning regulation, while the structural-transformation perspective captures how AI reshapes the broader learning environment and conditions of interaction.

Rather than treating these perspectives as competing explanations, the present model connects them through the mediating role of learner engagement.

The model therefore advances a central proposition: AI-enabled learning transformation is best understood as a mediated process in which contextual environments shape behavioral and psychological engagement and, through that engagement, contribute to competence development.

4. Discussion

The contribution of the present study lies not only in proposing a conceptual model of AI-enabled learning but also in clarifying how AI-enabled learning environments become educationally consequential. As the preceding review has shown, research on AI in higher education has expanded rapidly, yet the field has remained more effective at documenting technological functions and structural changes than at explaining the learner-level mechanisms through which these changes produce developmental outcomes. The framework proposed here addresses this limitation by integrating environmental conditions, engagement processes, and competence development into a single explanatory structure. As illustrated in Figure 1, the model explains how AI-enabled learning environments influence competence development through the mediating processes of behavioral and psychological engagement.

A first contribution of the study is that it extends the Stimulus-Organism-Response (S-O-R) framework into the domain of AI-enabled higher education in a way that is analytically substantive rather than merely terminological. Previous studies in AI-supported education have shown that intelligent systems can improve feedback, personalize support, and reorganize instructional settings, but they have been less explicit about the internal pathway through which these environmental conditions influence learning. By conceptualizing AI-enabled learning environments as contextual stimuli and by treating learners' behavioral and psychological engagement as the mechanism through which those stimuli are processed, the present study provides a clearer explanation of how technological environments become pedagogically effective. In this sense, the model does more than apply an established framework

to a new context; it demonstrates why the S-O-R framework is particularly well suited to explaining AI-enabled learning transformation, namely because it foregrounds the mediating role of engagement in linking environment and development.

A second contribution is that the study brings together two strands of research that are often discussed separately in the AI-in-education literature. On the one hand, the process-optimization perspective has generated important evidence about how AI can enhance feedback, monitor progress, and support adaptive learning. On the other hand, the structural-transformation perspective has shown that AI can reshape learning spaces, pedagogical design, and forms of participation. These perspectives are often treated as competing interpretations of AI in education. The present model suggests otherwise. It indicates that they address different layers of the same educational process: AI may restructure learning environments and optimize instructional processes, but its educational effects ultimately depend on how these changes shape learners' engagement. In this respect, the study does not simply juxtapose two perspectives; it provides a mechanism-based explanation of how they can be theoretically integrated.

A third contribution concerns the way learning outcomes are conceptualized in AI-enabled educational contexts. Much of the existing literature continues to evaluate educational value primarily in terms of performance indicators such as achievement gains, task completion, or efficiency improvement. While such indicators remain useful, they are limited for understanding learning in AI-enabled interdisciplinary environments, where learners increasingly confront complexity, uncertainty, and collaborative problem solving. By conceptualizing the response dimension of the model as competence development, the present study shifts the analytical focus from short-term performance to more durable educational outcomes, including problem-solving ability, interdisciplinary integration, and self-regulated learning. This shift aligns the analysis of AI-enabled learning with broader developments in higher education, where emphasis is increasingly placed on complex capability formation rather than narrow performance improvement.

This interpretation is consistent with recent research indicating that generative AI can

support a broader range of academic outcomes—including critical thinking, problem-solving, motivation, and self-efficacy—rather than merely improving short-term performance indicators [20]. The same meta-analysis also suggests that the effects of generative AI on college students' academic achievement are generally positive but vary across contexts, depending on instructional design, activity type, and the nature of generated content.

At a broader level, the model also helps explain why debates about AI in education often oscillate between optimism and concern. AI-enabled learning environments can facilitate personalized support, collaborative inquiry, and adaptive regulation, but they may also create risks such as learner dependency, reduced opportunities for autonomous reflection, or the reinforcement of ability stratification. The present framework suggests that these tensions cannot be understood solely at the level of technological functionality. Rather, the educational implications of AI depend on how learners engage with these environments behaviorally and psychologically, and on how that engagement is shaped by contextual conditions. In this sense, the model not only explains positive educational outcomes but also provides a conceptual basis for examining the boundaries and risks of AI-enabled education. Recent research has similarly cautioned that excessive reliance on generative AI may undermine creativity and critical thinking [2,3], concerns that are also reflected in recent meta-analytic discussions of AI-supported learning [20].

Despite these contributions, several limitations of the present study should be acknowledged. First, the proposed model remains conceptual and therefore requires empirical examination. Future research could test the relationships among contextual stimuli, engagement processes, and competence development through mixed-methods designs that combine learning analytics, behavioral observation, and self-report measures. Such work would help clarify whether behavioral and psychological engagement operate as reciprocal, sequential, or context-specific processes within AI-enabled learning environments.

Second, although the model recognizes AI-enabled learning environments as relational environments, it focuses primarily on learners and gives limited analytical attention to the role of teachers. This is an important limitation, especially given increasing evidence that AI is reshaping teachers' work not only as instructors but also as designers, facilitators, and evaluators of learning. Future studies should therefore examine whether teacher agency functions as a contextual condition, a mediating process, or a boundary factor within AI-enabled learning environments.

Third, the model has been developed primarily with higher education and interdisciplinary learning in mind. Its applicability to other educational contexts therefore requires further examination. AI-enabled learning in primary or secondary education, vocational settings, or discipline-specific environments may involve different forms of participation, authority, and dependence. Future research should explore the extent to which the present framework can travel across contexts and where adaptation may be required.

Taken together, these limitations do not diminish the value of the model; rather, they indicate where its explanatory potential can be refined and extended. The central argument of the study remains that AI-enabled learning transformation should be understood not as a direct consequence of technological adoption but as a mediated process in which contextual environments shape learner engagement and, through that engagement, contribute to competence development.

5. Conclusion

This study addresses an increasingly important question in research on artificial intelligence and higher education: how do AI-enabled learning environments facilitate learning transformation? While existing studies have generated substantial knowledge about the functions of AI tools and the structural changes they introduce into teaching and learning, they have been less explicit about the mechanisms through which these changes become educationally meaningful. To address this gap, the present study developed a theoretical model based on the Stimulus-Organism-Response (S-O-R) framework. The model conceptualizes AI-enabled learning environments as contextual stimuli, learners' behavioral and psychological engagement as organism variables, and competence development as the response. This framework suggests that the impact of AI on higher education cannot be adequately understood in

terms of technological innovation alone. What matters is not simply the presence of AI tools but how AI-enabled learning environments structure the conditions under which learners participate, interpret tasks, persist in activities, and develop competencies.

By integrating the process-optimization and structural-transformation perspectives within a single explanatory framework, the study contributes to a more coherent understanding of AI-enabled education. It also shifts the discussion of learning outcomes away from narrow performance indicators and toward competence development, thereby aligning the analysis of AI-enabled learning with broader educational goals related to problem solving, interdisciplinary integration, and self-regulated learning.

More broadly, the study calls for a conceptual shift in the field. AI in education should not be viewed solely as a matter of tool effectiveness or system efficiency. It should also be understood in terms of how learning environments are reorganized and how learners' internal engagement processes are shaped within those environments. From this perspective, the educational significance of AI lies not only in technological capability but in how AI-enabled learning environments shape the conditions under which learners engage, interpret, and develop competencies.

Future research can build on this framework in two main ways. First, empirical studies are needed to examine how the proposed stimulus, organism, and response dimensions interact across different higher education contexts. Second, further work should investigate the conditions under which AI-enabled learning environments foster development rather than dependency, and inclusion rather than stratification. Addressing these questions will be essential if AI is to contribute not only to technological advancement in higher education but also to more meaningful, equitable, and competence-oriented forms of learning.

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