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Reconsidering Learning Styles in the Age of Artificial Intelligence: A Critical Review and Conceptual Discussion

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ABSTRACT

Learning styles have long been widely used in the educational literature to explain individual differences and to support the personalization of instruction. However, these approaches have been subject to significant empirical and theoretical criticism in recent years, largely due to the assumption that learning styles represent stable and instructionally dominant characteristics. At the same time, the rapid proliferation of artificial intelligence (AI)-supported learning environments has necessitated a reconsideration of learning as an adaptive, contextual, and process-oriented phenomenon. In this context, how AI structures learning experiences and what this implies for the concept of learning styles remain conceptually underexplored. The aim of this study is to critically reexamine the learning styles literature in the age of AI and to discuss how AI-mediated learning environments transform this concept. The study reviews classical approaches to learning styles and the major critiques directed at them, and then examines the underlying logic of personalization in AI-based adaptive learning systems. In the critical discussion, it is argued that the widespread claim that AI "changes" learning styles is based on assumptions that treat learning styles as fixed traits. Instead, learning in AI-supported environments is conceptualized as a dynamic, context-sensitive, and temporally evolving process. The paper proposes that learning styles should be reconceptualized not as stable individual traits but as dynamic learning orientations that emerge within AI-mediated learning processes. It is suggested that this conceptual shift provides a more explanatory framework for understanding learning in contemporary educational contexts and offers important implications for instructional design and future empirical research.

Keywords: learning styles, artificial intelligence, adaptive learning, learning orientations, personalized learning

INTRODUCTION

Learning styles have long occupied a central position in the educational literature as a means of explaining individual differences in learning and adapting instructional processes to learners' characteristics. These approaches are grounded in the assumption that individuals exhibit relatively consistent patterns in how they perceive, process, and construct knowledge, and that these patterns provide meaningful guidance for instructional decisions (Dunn & Dunn, 1993; Kolb, 1984). Models based on learning styles have been closely associated with learner-centered pedagogical approaches, particularly in the fields of instructional design and teacher education; in this respect, learning styles have been regarded as one of the theoretical foundations of personalized instruction (Coffield et al., 2004).

However, the assumptions underlying the instructional effectiveness of learning styles have increasingly been subjected to critical scrutiny over the past two decades. Experimental studies and systematic reviews examining the impact of instruction tailored to learning styles have revealed a lack of consistent and robust empirical evidence supporting these approaches (Pashler et al., 2008). These findings suggest that the common assumption that learning styles represent stable, immutable, and instructionally dominant characteristics may be problematic. Indeed, research emphasizing the sensitivity of learning to situational variables—such as task type, content structure, and learning context—indicates that learning styles alone do not provide a sufficient explanatory framework for instructional decision-making (Kirschner & van Merriënboer, 2013; Kirschner, 2017).

Rather than rejecting the role of individual differences in learning processes altogether, these critiques call for a more cautious and process-oriented approach to how such differences are conceptualized. Contemporary learning theories conceptualize learning not merely as a function of individual traits but as a dynamic process shaped by the interaction of cognitive, social, and contextual factors. From this perspective, there is a growing view that learning styles should be understood not as fixed categories but as tendencies or orientations that emerge within specific learning situations.

In a context where theoretical debates on learning styles have intensified, the rapid development of AI-supported learning environments has further challenged established assumptions about how learning should be personalized. AI-based learning systems are capable of continuously analyzing learners' behaviors, performance levels, and interaction patterns, and can adapt learning content, tasks, and feedback in real time based on these analyses (Luckin et al., 2016). Such systems implement personalization not through predefined individual characteristics, but through the ongoing interaction between the learner and the learning environment (OECD, 2023).

This shift reveals a significant conceptual gap regarding how learning styles should be understood in the age of artificial intelligence. Prevailing claims that AI "changes" or "transforms" learning styles often rely on traditional assumptions that treat learning styles as stable individual traits. However, AI-mediated learning environments structure learning not through static attributes, but through dynamic processes, feedback loops, and context-sensitive adaptations (Dede, 2014). From this perspective, the central question is not whether AI alters learning styles, but whether the concept of learning styles continues to provide an adequate explanatory framework in AI-supported learning contexts.

The aim of this study is to critically reexamine the learning styles literature in the age of AI and to explore the potential for reconceptualizing learning styles not as fixed individual traits, but as dynamic learning orientations that emerge within AI-mediated learning processes. To this end, the study systematically reviews classical approaches to learning styles and the main critiques directed at them, examines the logic of personalization in AI-based adaptive learning systems, and offers a conceptual discussion that integrates these two strands of literature.

Learning Styles: Conceptual Approaches and Critiques

The concept of learning styles emerged as a response to efforts to explain differences in how individuals learn and to adapt instruction accordingly. This perspective is based on the assumption that learners exhibit relatively consistent patterns in how they perceive, process, and construct knowledge, and that these patterns can be meaningfully incorporated into instructional design. Models of learning styles have been closely associated with approaches such as personalized instruction, learner-centered education, and differentiated instruction, which have contributed to their widespread use in educational practice (Coffield et al., 2004).

A review of the learning styles literature reveals a wide range of models grounded in different theoretical perspectives. One of the most influential is the experiential learning approach, which conceptualizes learning as a cyclical process consisting of concrete experience, reflective observation, abstract conceptualization, and active experimentation, and suggests that individuals may exhibit different preferences within this cycle (Kolb, 1984). Similarly, the model developed by Dunn and Dunn (1993) conceptualizes learning style as a multidimensional construct encompassing environmental, emotional, sociological, and physiological factors, and argues that aligning instruction with these preferences can lead to improved learning outcomes.

Such models have provided a compelling response to critiques of one-size-fits-all approaches to teaching, emphasizing that learners are not homogeneous and that instruction based on the assumption of an "average student" is pedagogically inadequate. In this sense, learning styles have offered educators a practical framework for recognizing and addressing individual differences in classroom settings. Regardless of their theoretical limitations, learning styles have thus played a significant role in educational practice by promoting greater sensitivity to learner diversity (Coffield et al., 2004).

However, the assumptions underlying the effectiveness of instruction based on learning styles have been increasingly questioned. Experimental studies examining the impact of instruction tailored to learning styles have shown that robust and consistent empirical evidence supporting these approaches remains limited. In their systematic review, Pashler et al. (2008) concluded that there is no convincing experimental evidence demonstrating that matching instruction to learners' styles leads to improved academic achievement.

These criticisms are also aligned with broader theoretical concerns regarding the treatment of learning styles as fixed and stable individual traits. Research highlighting the context-dependent nature of learning suggests that individuals may adopt different strategies and approaches depending on the task, content, and learning environment. Consequently, the use of rigid learning style categories appears insufficient for capturing the complexity of learning processes (Kirschner & van Merriënboer, 2013). In this regard, Kirschner (2017) argues that learning styles have become a pedagogical "urban myth" and that their uncritical use in instructional design may lead to misguided educational practices.

REVISITING CRITIQUES OF LEARNING STYLES

The critiques directed at learning styles do not necessarily require the conclusion that the concept is entirely invalid. Rather, these critiques point to the need for a more nuanced understanding of how learning styles should be conceptualized and positioned within instructional processes. The central issue is not the existence of individual differences per se, but the tendency to treat these differences as fixed, generalizable, and instructionally determinative characteristics (Coffield et al., 2004; Pashler et al., 2008).

From this perspective, reconceptualizing learning styles not as immutable traits but as tendencies or orientations that emerge within specific learning contexts offers a more explanatory approach. Such a reinterpretation foregrounds the temporal, contextual, and interactional nature of learning, enabling learning styles to be understood within a process-oriented framework. Rather than rejecting the learning styles

literature altogether, this perspective seeks to reposition it within a broader and more dynamic understanding of learning.

This theoretical reconsideration becomes even more significant with the rise of AI-supported learning environments. AI-based systems do not adapt learning based on predefined individual characteristics; instead, they continuously adjust instruction through ongoing interactions between the learner and the learning environment. This shift renders the treatment of learning styles as fixed categories increasingly problematic. In this context, critiques of learning styles can be seen as a starting point for a broader reconsideration of how learning should be conceptualized in the age of artificial intelligence.

The Emergence of the Learning Styles Concept

The concept of learning styles emerged as a response to efforts to explain differences in how individuals learn and to make instructional processes more responsive to these differences. For a long time, education was largely structured around the assumption of an "average learner," which led to the neglect of individual variability in learning. This assumption began to be increasingly challenged, particularly in the second half of the twentieth century, as psychological and pedagogical research demonstrated that individuals differ in how they perceive, process, and construct knowledge, and that learning cannot be adequately explained through uniform models (Messick, 1994; Sternberg & Zhang, 2001).

Within this context, learning styles were developed as a concept aimed at describing learners' preferred cognitive and behavioral tendencies in learning processes. Early studies sought to distinguish these tendencies from relatively stable constructs such as personality traits or general intelligence, instead focusing on dimensions intrinsic to the learning process itself. This shift reinforced the idea that understanding learning requires attention not only to what is learned, but also to how learning occurs (Coffield et al., 2004).

The widespread adoption of the learning styles concept was closely linked to the rise of learner-centered approaches in education, which emphasized individual differences. As behaviorist models—largely focused on external stimuli and standardized outcomes—gave way from the 1960s onward to cognitive and constructivist perspectives, greater emphasis was placed on the active role of the learner, prior knowledge and experience, and individual learning preferences. This paradigmatic shift positioned learners at the center of instructional design and foregrounded the importance of accommodating individual variability (Biggs, 1993; Entwistle, 2013).

In this process, learning styles came to be widely accepted as a pedagogical tool within learner-centered education. It was assumed that identifying learners' styles would contribute to the personalization of instruction and the design of more flexible learning environments. Particularly in teacher education and classroom practice, learning styles provided a practical framework for helping educators recognize diverse learning needs and diversify their instructional strategies (Coffield et al., 2004).

However, this positioning also introduced a tension between the pedagogical utility of learning styles and their theoretical foundations. Over time, the tendency to treat learning styles as fixed categories guiding instructional decisions led to criticisms that such approaches overlook the dynamic and context-dependent nature of individual differences. Nevertheless, when considered in light of their historical origins, it becomes clear that the primary aim of the learning styles concept was not to label learners, but to make instruction more responsive to individual differences (Messick, 1994).

Accordingly, the emergence of the learning styles concept should be understood not merely in terms of the development of specific models, but as part of a broader pedagogical transformation that foregrounded individual differences and learner-centered education. This historical and conceptual context provides an

important foundation for interpreting contemporary critiques of learning styles in a more informed and balanced manner.

Classical Models of Learning Styles

The learning styles literature has evolved through the development of numerous models grounded in diverse theoretical perspectives, all of which share a common aim: to identify learners' preferred ways of engaging in the learning process and to inform instructional design accordingly. However, these models differ substantially in how they conceptualize learning, the dimensions along which they define individual differences, and the pedagogical implications they propose (Coffield et al., 2004).

Among these approaches, the experiential learning model offers one of the most influential frameworks. It conceptualizes learning as a cyclical process emerging from the interaction between the individual and experience, consisting of four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 1984; Kolb & Kolb, 2005). By suggesting that individuals may demonstrate different preferences within this cycle, the model emphasizes that learning is not solely cognitive but also experiential and process-oriented. In this respect, it provides a strong foundation for incorporating diverse learning activities into instructional design.

In contrast, multidimensional approaches to learning styles—exemplified by the Dunn and Dunn model—conceptualize learning style as a complex construct extending beyond cognitive preferences to include environmental, emotional, sociological, and physiological factors (Dunn & Dunn, 1993). Such models have offered educators practical guidance for recognizing individual differences and diversifying instructional strategies in classroom settings, which has contributed to their widespread adoption in educational practice (Coffield et al., 2004).

However, defining learning styles across multiple dimensions has also introduced challenges related to conceptual clarity and measurement validity. The expansion of the concept has often blurred its boundaries, leading to overgeneralizations in pedagogical applications. As a result, questions have emerged regarding the extent to which learning styles provide a reliable basis for instructional decision-making (Coffield et al., 2004).

Despite these limitations, classical models of learning styles have made a significant contribution by increasing educators' awareness of individual differences and by challenging one-size-fits-all approaches to teaching. Yet, the failure to distinguish between their pedagogical utility and their theoretical validity has led to the problematic use of learning styles as if they were scientifically validated prescriptions for instruction, ultimately reinforcing their treatment as fixed categories. Therefore, these models should be evaluated with their limitations in mind, and their primary value should be recognized in their emphasis on the multidimensional and variable nature of learning across individuals.

Empirical and Theoretical Critiques

Critiques of learning styles are largely grounded in the limited empirical evidence supporting the instructional effectiveness of these approaches. A widely held assumption in the literature is that individuals possess distinct learning styles and that aligning instruction with these styles leads to improved learning outcomes. However, recent reviews and meta-analyses indicate that robust and consistent evidence supporting this assumption remains insufficient (Cuevas, 2015; Newton & Salvi, 2020). Experimental studies have generally failed to demonstrate a systematic advantage for instruction tailored to learning styles, and the findings that do exist are often constrained by methodological limitations. In particular, small sample sizes, concerns regarding the validity of measurement instruments, and research designs that do not permit causal inference have weakened the empirical foundation of this line of research (Aslaksen & Lorås, 2018). Consequently, the

question of whether learning styles provide a reliable basis for instructional decision-making continues to be debated in the contemporary literature.

The lack of strong empirical support has also led to increasing criticism of the portrayal of learning styles as an evidence-based approach in educational practice. In this context, learning styles have been described by some scholars as a pedagogical "myth" (Newton & Salvi, 2020). Their widespread acceptance among teachers and educators is often attributed to their intuitive appeal and ease of application. However, this popularity also raises concerns that instructional decisions may be guided more by intuitive assumptions than by scientific evidence. As such, the tension between the pedagogical popularity and the scientific validity of learning styles remains a central issue.

A key dimension of the theoretical critique concerns the treatment of learning styles as fixed and stable individual traits. Contemporary research on learning suggests that individuals adopt different strategies depending on the task, content, and learning environment, and that learning behaviors are inherently context-dependent (Kirschner & Hendrick, 2024; Nancekivell et al., 2020). From this perspective, defining learning styles independently of context appears overly reductionist. Moreover, labeling learners according to fixed styles may restrict their opportunities to explore alternative learning strategies and to develop cognitive flexibility. Instructional approaches that prioritize such fixed categories over learning goals and content structure may therefore lead to pedagogically problematic outcomes.

Taken together, these empirical and theoretical critiques suggest that the core issue is not the existence of individual differences, but rather how these differences are conceptualized and utilized within instructional processes. Treating learning styles as stable individual traits is inconsistent with the dynamic, contextual, and process-oriented nature of learning. Accordingly, rather than abandoning the concept altogether, there is a need to reconsider it within a more flexible and process-oriented framework.

Reconceptualizing Learning Styles

Empirical and theoretical critiques of learning styles do not necessarily call for abandoning the concept altogether; rather, they provide important insights into how it might be reconceptualized. An increasingly influential view in the literature is that treating learning styles as stable and context-independent traits fails to adequately capture the nature of learning. Accordingly, learning styles should be reconsidered not as fixed individual characteristics, but as tendencies that emerge under specific learning conditions and evolve over time (Messick, 1994; Sternberg & Zhang, 2001). Recent research further supports this view, demonstrating that learning behaviors are sensitive to context, task demands, and interactions within the learning process (Kirschner & Hendrick, 2024; Nancekivell et al., 2020). Moreover, studies emphasizing the dynamic and adaptive nature of learning suggest that individual differences are more appropriately understood as patterns that develop within processes rather than as static categories (Holmes et al., 2019; OECD, 2023). From this perspective, reconceptualizing learning styles requires a more flexible and process-oriented approach that accounts for the temporal and contextual dimensions of learning.

One of the central assumptions of classical learning style theories is that individuals possess a particular style that is relatively stable across different learning situations. However, this assumption has increasingly been challenged by evidence showing that learners adopt different strategies depending on the task, content, and learning environment. Research highlighting the situational and context-dependent nature of learning behaviors suggests that treating learning styles as fixed personal attributes is overly reductionist (Biggs, 1993; Entwistle, 2013).

From this standpoint, the use of learning styles as immutable labels that categorize individuals appears problematic both theoretically and pedagogically. The assumption that learners "have" a particular style may restrict their willingness to explore alternative approaches and develop new strategies. Consequently, such

labeling practices risk overlooking the importance of flexibility and adaptability in the learning process (Coffield et al., 2004).

Alternative perspectives on learning styles conceptualize them as context-dependent tendencies or orientations rather than fixed traits. Within this view, learning styles reflect learners' preferences in specific learning situations, shaped by the interaction of prior experiences, learning goals, task characteristics, and environmental conditions (Sternberg & Zhang, 2001). This contextual interpretation allows learning styles to be examined in relation to questions such as when, under what conditions, and for what purposes particular learning tendencies emerge. As a result, learning styles are no longer understood as general attributes that explain all learning behaviors, but as temporary orientations that arise within specific contexts. This approach provides a more explanatory framework by acknowledging the dynamic and situational nature of individual differences without dismissing their relevance (Messick, 1994).

TOWARDS A DYNAMIC CONCEPTION OF LEARNING

Reinterpreting learning styles as context-dependent tendencies aligns with a broader, dynamic understanding of learning. Contemporary research conceptualizes learning not as a mechanical outcome of individual traits, but as a process shaped by the interaction between the learner, the task, and the context. This perspective highlights that learning behaviors evolve over time and that individuals can adapt to different learning situations (Kirschner & Hendrick, 2024; Nancekivell et al., 2020).

Within this framework, the reconceptualization of learning styles supports a pedagogical approach that emphasizes flexibility and adaptability in the learning process. Rather than treating learning styles as fixed categories in instructional design, it becomes more meaningful to create rich learning environments that enable learners to experience and shift among different learning orientations. Recent studies indicate that effective learning is associated with the capacity to move flexibly between multiple strategies (Holmes et al., 2019; OECD, 2023). From this perspective, the aim is not to reject the learning styles literature altogether, but to reposition it within a broader and more dynamic understanding of learning.

This reinterpretation becomes even more significant with the rise of AI-supported learning environments. AI-based systems structure learning not according to predefined individual traits, but through real-time interactions and feedback processes. As a result, learning becomes a continuously adaptive and data-driven process (Luckin et al., 2016; OECD, 2023). Accordingly, conceptualizing learning styles as dynamic learning orientations offers a more explanatory framework for understanding learning in the age of artificial intelligence.

ARTIFICIAL INTELLIGENCE AND ADAPTIVE LEARNING

The development of AI-supported learning environments has significantly transformed established understandings of how learning can be personalized. In parallel with critiques of learning styles as fixed individual traits, AI-based systems conceptualize learning not through static categories, but through continuously updated processes. This section examines the core characteristics of AI-supported learning systems, the transformation of personalization, and the relationship between artificial intelligence and individual differences.

Core Features of AI-Supported Learning Systems

A defining feature of AI-supported learning systems is their capacity to monitor learning processes through data-driven approaches and to adapt learning experiences accordingly. Unlike traditional learning environments, these systems model the learner not in terms of static attributes, but through patterns of behavior and performance that emerge during the learning process (VanLehn, 2011; Woolf, 2010).

Student modeling lies at the core of AI-based learning systems. It involves the continuous tracking and updating of variables such as learners' knowledge states, error patterns, learning pace, and interaction behaviors. These models aim to capture not who the learner is, but how the learner learns and where they are within the learning process (Graesser et al., 2012). In this sense, student modeling fundamentally differs from static profiling approaches based on learning styles.

Data-driven adaptation constitutes another key feature of AI-supported systems. Information derived from learners directly influences the sequencing of content, the level of difficulty, the mode of presentation, and the types of learning tasks provided. Rather than relying on predefined rules, such adaptations are driven by patterns that emerge during the learning process itself (Baker & Inventado, 2014, Luckin et al., 2016).

Immediate feedback is also a critical component of AI-supported learning environments. These systems can respond to learners' performance in real time, providing guidance that shapes the ongoing learning process. Real-time feedback supports the continuity of learning and enables learners to regulate their own learning more effectively (VanLehn, 2011). This capability contributes to the temporal dynamism of learning by allowing it to be continuously adjusted and refined as it unfolds.

The Transformation of Personalization

With the widespread adoption of AI-supported learning environments, the concept of personalization in education has undergone a significant transformation. Traditional approaches to personalization have often been limited to adaptations based on predefined learner characteristics or categorizations that group learners according to certain traits. Within this framework, learning styles have frequently served as one of the primary reference points for personalization (Coffield et al., 2004).

Traditional personalization aims to define learners based on specific attributes and to adapt instruction accordingly. In this approach, personalization is typically confined to measurements conducted prior to instruction and does not sufficiently account for changes that emerge during the learning process. As a result, personalization tends to remain static and limited in scope.

In contrast, AI-based personalization conceptualizes learning not in terms of predefined profiles, but through the interaction among the learner, the task, and the context. By continuously monitoring the learning process, AI systems transform personalization into a dynamic and ongoing process, restructuring the learning experience in real time (Dede, 2014; OECD, 2023). In this model, personalization is responsive to learners' evolving needs and learning behaviors over time.

This transformation requires a shift in how personalization is conceptualized—from the question of "for whom?" to "under what learning conditions, and what kind of adaptation?" Consequently, personalization becomes a more flexible and context-sensitive construct, centered on the dynamics of the learning process itself.

Artificial Intelligence and Individual Differences

AI-supported learning environments do not disregard individual differences; rather, they fundamentally transform how these differences are conceptualized and addressed. In this respect, there are both points of convergence and divergence between artificial intelligence and learning styles. Both perspectives acknowledge the existence of variability among learners and challenge one-size-fits-all approaches to instruction. AI-based systems, for instance, leverage data-driven analyses to identify differences in learners' pace, error patterns, and interaction behaviors, and incorporate these variations into the instructional process (Chukwu et al., 2026; Woolf, 2010).

However, the key distinction between these approaches lies in how individual differences are conceptualized. Learning styles are often defined as relatively stable traits that individuals possess, whereas AI-supported systems treat learning behaviors as dynamic, evolving, and context-sensitive patterns that emerge over time. Through student modeling and learning analytics, AI systems continuously update representations of learners' performance based on temporal and contextual variables, thereby framing learning as an ongoing and adaptive process (Adhikari et al., 2025; VanLehn, 2011).

Accordingly, in AI-supported learning environments, individual differences are approached from a process-oriented perspective rather than as fixed attributes. Learning behaviors evolve as the learning process unfolds, and learners may adopt different strategies in response to varying tasks and contexts. Recent research indicates that AI-powered learning tools dynamically shape learner engagement and behavior by continuously monitoring and responding to interactions within the learning process (Chukwu et al., 2026; OECD, 2023).

From this perspective, artificial intelligence should not be understood as a force that "changes" learning styles, but rather as an environment that continuously restructures learning itself. The transformative impact of AI-supported systems on pedagogical processes enables instructional design to become more flexible, data-driven, and context-sensitive (Selamet, 2026). This shift necessitates conceptualizing learning not in terms of fixed categories but as dynamic structures that evolve, thereby supporting the reconceptualization of learning styles as dynamic learning orientations (Holmes et al., 2019; OECD, 2023).

CRITICAL DISCUSSION: DOES ARTIFICIAL INTELLIGENCE CHANGE LEARNING STYLES?

With the widespread adoption of AI-supported learning environments, the question of how learning styles should be understood in this new context has become a central issue of debate. In particular, the question "Does artificial intelligence change learning styles?" is frequently raised in both academic discourse and practice-oriented discussions. However, this question implicitly rests on a set of assumptions regarding the nature of learning styles. The traditional view that learning styles represent stable characteristics that individuals possess and maintain over time has long shaped the literature, and studies across different disciplines have documented consistent learner preferences (Varışoğlu, 2018; Yavuzalp & Gürol, 2017). Nevertheless, the treatment of these preferences as context-independent and immutable traits has increasingly been challenged from both theoretical and empirical perspectives. Indeed, recent efforts to update learning style classifications suggest that learning styles should be understood as constructs that evolve alongside learning processes rather than as fixed categories (Gencel & Erdoğan, 2022).

Within this context, the question of whether AI "changes" learning styles is grounded in a framework that treats them as directly modifiable entities. However, such a perspective overlooks the ongoing uncertainty surrounding the ontological status of learning styles. Even studies examining the relationship between learning styles and academic achievement indicate that this relationship is context-dependent and limited, with learning behaviors varying across different learning environments (Agustino & Pertiwi, 2021; Sidekli & Akdoğdu, 2018). In particular, research conducted in online and e-learning settings demonstrates that learners' preferred approaches are shaped by technological conditions, content characteristics, and interaction patterns (Dalmolin et al., 2018). These findings suggest that learning styles are better understood not as fixed traits, but as patterns that emerge within the learning process and vary according to context.

At this point, a significant conceptual shift becomes evident. The adaptive capabilities of AI-supported systems are often interpreted as transforming learning styles; however, such adaptations do not target an assumed underlying style. Rather, they operate on patterns of performance, interaction, and feedback that emerge during the learning process. It is therefore essential to distinguish between the "modification" of

learning styles and the contextual reconfiguration of learning behaviors. This distinction enables learning styles to be conceptualized not as stable individual attributes, but as evolving orientations that emerge over time within specific learning contexts.

From this perspective, the reinterpretation of learning styles requires a shift from the notion of "style" to that of "learning orientations." While the concept of style tends to categorize individuals into predefined types, learning orientations capture the transient tendencies and preferences that arise within the learning process. This approach allows learning to be understood not as a mechanical outcome of individual traits, but as a dynamic process shaped by the interaction among the learner, the task, and the context. Furthermore, the practice of labeling learners based on learning styles must be critically reconsidered. Assigning learners to fixed categories risks constraining their learning trajectories, whereas the notion of learning orientations conceptualizes learning as an evolving process that can develop in multiple directions over time.

In conclusion, discussions of learning styles in the age of artificial intelligence should move beyond reductionist questions such as whether AI "changes" learning styles, and instead focus on how learning itself is conceptualized. Reconceptualizing learning styles as dynamic and context-sensitive learning orientations offers a more coherent theoretical framework and provides a more functional basis for both instructional design and educational practice.

The Role of Artificial Intelligence in Shaping Learning Orientations

AI-supported learning environments provide a compelling context for operationalizing the concept of learning orientations. Rather than adapting instruction based on predefined individual characteristics, these systems tailor learning experiences according to behavioral patterns that emerge during the learning process. Task-based adaptation is a central mechanism in this regard, as learning content and activities are continuously restructured based on learners' performance and their interaction with specific tasks (Baker & Inventado, 2014; Woolf, 2010).

This dynamic structure supports the development of cognitive flexibility within the learning process. Instead of confining learners to a single pathway, AI-supported systems expose them to a range of strategies and problem-solving approaches. Such exposure enables learners to expand their learning orientations and to experiment with alternative ways of engaging with learning tasks (Dede, 2014).

Finally, AI-supported learning environments conceptualize learning as a continuously evolving process. Learning orientations are not fixed within this process; rather, they are reshaped and reconfigured as the learning experience unfolds. In this sense, artificial intelligence should not be understood as a mechanism that "changes" learning styles, but as a learning ecosystem that continuously reorganizes learning orientations. This perspective provides a strong conceptual foundation for rethinking the role of learning styles in the age of artificial intelligence.

IMPLICATIONS FOR FUTURE RESEARCH

Future research should prioritize experimental investigations that examine how learning orientations emerge within AI-supported learning environments and how these orientations relate to learning outcomes. In particular, experimental designs comparing adaptations based on learning styles with process-oriented adaptations could provide valuable insights into the relative effectiveness of these approaches.

Given the dynamic nature of learning orientations, short-term and single-measure studies offer limited explanatory power. Longitudinal research is therefore essential for capturing how learning orientations evolve over time and for examining the impact of AI-driven adaptations on these changes. Such studies can illuminate

the developmental nature of learning and provide stronger evidence challenging the assumption of stability underlying traditional learning styles frameworks (Entwistle, 2013).

Another important direction for future research involves a more detailed examination of how AI-supported systems shape learning behaviors. The effects of student modeling, feedback mechanisms, and adaptation strategies on learner behavior can be investigated from a learning orientations perspective. Rather than focusing on whether AI "changes" learning styles, such research has the potential to generate more meaningful insights into how learning itself is structured within AI-mediated environments (Baker & Inventado, 2014; OECD, 2023). In this regard, studies that integrate the learning styles literature with research on AI-supported learning are likely to contribute to the development of a more balanced and evidence-informed understanding of personalization in education.

CONCLUSION

This study aimed to critically reexamine the concept of learning styles within the emerging learning contexts shaped by the age of artificial intelligence. While learning styles have long been used in the educational literature to explain individual differences and to support personalized instruction, treating them as fixed and immutable traits presents significant empirical and theoretical limitations. Accordingly, this study argues not for the rejection of the concept but for its repositioning within a more dynamic and process-oriented framework.

In this process of reconceptualization, AI-supported learning environments provide an important conceptual foundation for revisiting the role of learning styles. Rather than functioning as tools that adapt instruction based on predefined learner profiles, AI systems operate as learning ecosystems that continuously monitor learning processes, restructure them through feedback loops, and regulate learning experiences in context-sensitive ways. From this perspective, artificial intelligence should not be understood as a factor that "changes" learning styles, but as a context that transforms how learning itself is structured (Dede, 2014; OECD, 2023).

This transformation points to a broader paradigm shift in how learning is understood. Learning is no longer viewed as a reflection of stable individual traits, but as a process that evolves over time through the interaction of the learner, the task, and the context. Within this perspective, learning styles are no longer treated as fixed categories, but as dynamic learning orientations that emerge within specific learning situations. This approach offers a more flexible framework that acknowledges individual differences while emphasizing their contextual and temporal nature (Messick, 1994; Sternberg & Zhang, 2001).

In conclusion, this study argues that discussions of learning styles in the age of artificial intelligence should move beyond reductionist questions such as whether AI "changes" learning styles. Instead, a more holistic perspective is needed—one that focuses on how learning is conceptualized and on the assumptions underlying instructional design. Reconceptualizing learning styles as dynamic learning orientations holds significant potential for providing a more explanatory and generative framework for both instructional practice and future empirical research.

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