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ARTICLE

FROM PERSONALIZED LEARNING TO HUMAN-CENTERED INTELLIGENT ENGAGEMENT: A CONCEPTUAL FRAMEWORK FOR AI-ENHANCED VIRTUAL LEARNING ENVIRONMENTS

Da Aprendizagem Personalizada ao Engajamento
Inteligente Centrado no Ser Humano: Um Framework
Conceitual para Ambientes Virtuais de Aprendizagem
Potencializados por Inteligência Artificial

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ABSTRACT | Background: Personalized learning using VLEs has evolved from pre-designed customizations of content, pace, and learning paths to smart, predictive, real-time personalization powered by learning analytics, adaptive techniques, conversational agents, and generative AI. However, technology adoption does not always translate into meaningful or sustained engagement. **Objective:** This paper investigates the relationship between personalized learning, AI-enabled VLEs, learner agency, self-regulated learning, human-centred pedagogy, and multidimensional student engagement, and proposes an integrated conceptual framework for human-centred intelligent personalization. **Methods:** A structured critical and thematic review approach was used in conjunction with the development of a conceptual framework. Relevant literature on personalized learning, VLEs, AI in education, learning analytics, adaptive learning, student engagement, learner agency, self-regulated learning, pedagogical functions, and the ethical and inclusive dimensions of intelligent educational technologies was conceptually tabulated. Common themes and relationships were identified and clustered thematically. **Results:** Five interrelated categories emerged from the synthesis: technological intelligence; learner agency and self-regulation; human-centred pedagogy; multidimensional student engagement behaviourally, cognitively, emotionally, and agentially; and ethical and sustainable foundations. These categories informed the Human-Centered Intelligent Engagement Framework (HCIEF), which conceptualizes intelligent personalization as a human-technology-pedagogy ecosystem rather than a linear technological process. The review also revealed a technology-agency dilemma: automation can increase system responsiveness at the cost of possibly reducing learners' ability to choose, reflect and self-regulate. **Conclusion:** HCIEF poses meaningful intelligent personalization as the coalescence of technical, human, pedagogical, and situational factors. It is technically challenging and also requires learner agency, pedagogical judgement, educational participation,





multidimensional engagement, as well as ethical, inclusive, and sustainable contextual frames. The framework offers a theoretically based foundation for the design, evaluation, and empirical investigation of next generation personalized VLEs.

Keywords | Artificial Intelligence; Personalized Learning; Virtual Learning Environments; Student Engagement; Learner Agency; Self-Regulated Learning; Human-Centered Pedagogy; Intelligent Personalization

RESUMO | Contexto: A aprendizagem personalizada em Ambientes Virtuais de Aprendizagem (AVAs) evoluiu de formas previamente estruturadas de adaptação de conteúdo, ritmo e trajetórias de aprendizagem para modalidades inteligentes, preditivas e dinâmicas de personalização em tempo real, apoiadas por learning analytics, tecnologias adaptativas, agentes conversacionais e inteligência artificial generativa. Contudo, a adoção dessas tecnologias nem sempre resulta em um engajamento significativo e duradouro. **Objetivo:** Este estudo investiga as relações entre aprendizagem personalizada, AVAs potencializados por inteligência artificial, agência do estudante, aprendizagem autorregulada, pedagogia centrada no ser humano e as múltiplas dimensões do engajamento discente, propondo um framework conceitual integrado para uma personalização inteligente centrada no ser humano. **Métodos:** Adotou-se uma abordagem de revisão crítica e temática estruturada, articulada ao desenvolvimento de um framework conceitual. A literatura relevante sobre aprendizagem personalizada, AVAs, inteligência artificial na educação, learning analytics, aprendizagem adaptativa, engajamento discente, agência do estudante, aprendizagem autorregulada, funções pedagógicas e dimensões éticas e inclusivas das tecnologias educacionais inteligentes foi organizada e analisada conceitualmente. Temas recorrentes e relações entre os conceitos foram identificados e agrupados em categorias temáticas. **Resultados:** A síntese revelou cinco categorias inter-relacionadas: inteligência tecnológica; agência do estudante e autorregulação; pedagogia centrada no ser humano; engajamento discente multidimensional, abrangendo as dimensões comportamental, cognitiva, emocional e agêntica; e fundamentos éticos e sustentáveis. Essas categorias fundamentaram o **Framework de Engajamento Inteligente Centrado no Ser Humano (EICSH)**, que compreende a personalização inteligente como um ecossistema integrado entre tecnologia, ser humano e pedagogia, e não como um processo tecnológico linear. A revisão também identificou um dilema entre automação e agência: embora a automação possa ampliar a capacidade de resposta dos sistemas, ela também pode reduzir as oportunidades de escolha, reflexão e autorregulação dos estudantes. **Conclusão:** O **EICSH** concebe a personalização inteligente significativa como resultado da integração entre fatores tecnológicos, humanos, pedagógicos e contextuais. Sua efetividade não depende apenas da sofisticação técnica, mas também da preservação da agência do estudante, do julgamento pedagógico, da participação ativa no processo educacional, do engajamento multidimensional e de referenciais éticos, inclusivos e sustentáveis. O framework oferece uma base teórica para o desenvolvimento, a avaliação e a investigação empírica da próxima geração de Ambientes Virtuais de Aprendizagem personalizados e mediados por inteligência artificial. **Palavras-chave** | Inteligência Artificial; Aprendizagem Personalizada; Ambientes Virtuais de Aprendizagem; Engajamento Discente; Agência do Estudante; Aprendizagem Autorregulada; Pedagogia Centrada no Ser Humano; Personalização Inteligente.

INTRODUCTION

Virtual learning environments (VLEs) have evolved substantially from platforms primarily designed for distributing instructional materials, facilitating communication, and managing assessment into increasingly interactive, adaptive, and data-informed learning ecosystems (Nguyen et al., 2017; Tao et al., 2025). This transformation has expanded the possibilities for tailoring learning experiences according to learners' prior knowledge, progress, interests, preferences, and goals. Within this context, personalized learning has increasingly been understood not simply as a technological feature, but as a learner-centered pedagogical approach that provides flexible learning pathways while supporting autonomy, agency, and self-regulation (Basham et al., 2016; Walkington & Bernacki, 2020).



Personalized learning is closely connected with student engagement. In VLEs, engagement extends beyond visible participation or completion of online activities and encompasses behavioral participation, cognitive investment, emotional involvement, and proactive contribution to the learning process (Fredricks et al., 2004; Reeve & Tseng, 2011). Research has associated engagement in online learning with satisfaction and perceived learning, while studies of personalized learning have emphasized the importance of motivation, affective involvement, and self-regulation in creating meaningful learning experiences (Gray & DiLoreto, 2016; Kim, 2012; Abedi et al., 2021). Thus, the educational value of personalization depends not merely on whether content or pathways are adapted, but on whether such adaptation contributes to deeper, sustained, and more agentic engagement.

The technological foundations of personalized VLEs have also undergone significant transformation. Learning analytics and adaptive systems have enabled environments to respond to learner behaviour and performance, while recommendation mechanisms, chatbots, immersive technologies, and AI-supported feedback have introduced increasingly interactive forms of personalization (Klašnja-Milićević et al., 2020; Colace et al., 2014; Marougkas et al., 2021; Baskara, 2023; Ayeni et al., 2024). More recently, generative artificial intelligence (GenAI) and large language models have expanded personalization towards conversational and generative forms of interaction, allowing systems to provide individualized explanations, questions, feedback, examples, and learning resources in response to learner inputs.

For the purposes of this paper, **personalized learning** refers to a learner-centered approach in which learning experiences, pathways, support, pacing, or resources are responsive to individual learner characteristics and needs. **Virtual learning environments** are understood as digital learning ecosystems that facilitate instructional interaction, resources, assessment, communication, and increasingly adaptive and intelligent forms of learning support. **Intelligent personalization** refers to the use of AI, learning analytics, adaptive technologies, conversational systems, and related capabilities to dynamically respond to learner information and provide individualized support. **Student engagement** is conceptualized as a multidimensional construct encompassing behavioral, cognitive, emotional, and agentic dimensions. These definitions provide the conceptual boundaries within which the present paper examines the relationship between intelligent personalization and engagement.

Even with these advances, there is, necessarily, a gap between technological intelligence and educational usefulness. An AI system can precisely identify the patterns of learners, suggest resources, or create tailored explanations but it still has to be evaluated pedagogically to assess if the experience it provides to the learner is suited for the learning objectives and the learner. The work on AI-generated personalized formative feedback indicates that AI can provide feedback at a similar pedagogical quality as the feedback written by a human, but also points to limitations in certain aspects of metacognitive support (Nazaretsky et al., 2026). Research on GenAI-enabled personalised learning also attests to persistent challenges in addressing the dynamic nature of learners, learning processes, and higher-order ends of education (Tu et al., 2025). Consequently, considering output from AI as individualized should not be conflated with pedagogy-based personalisation of learning. Due to this, the focus now is not that “can technology personalise learning” but rather “**how can intelligent personalisation enable deeper meaningful engagement without compromising learner agency and human pedagogical judgement?**”



This issue becomes particularly significant with the increasing incorporation of GenAI into educational environments. The personalized learning experiences enabled by AI can make learning and teaching environments more dynamic and efficient with content, feedback, and learning pathways adjusted in real time based on data about the learner. But more technical responsiveness does not always mean more learner agency. When thinking or deciding processes are outsourced to technological systems, learners do offload cognitively, i.e., they use external resources to do some of the mental labour of a task (Risko & Gilbert, 2016). In AI-facilitated learning environments, this worry is especially salient as students might depend on AI-produced suggestions or help instead of independently analyzing options and choosing courses of action related to learning. Early evidence from AI-enhanced education environments indicates that students may become over-reliant on AI support rather than learn from it, pointing to a potential conflict between technological support and student agency (Darvishi et al., 2024). Hence, whereas AI can improve responsiveness, too much or poorly designed automation could limit learner options and foster dependence on algorithmic advice. This call for a human-centric model of personalization where AI supports the agency of learners and educators and does not displace learner judgement or decision making. The educator consequently remains essential as a designer, facilitator, interpreter of learner information, and source of pedagogical and ethical judgement (Laurillard, 2013; Bishop et al., 2020). Personalized learning in contemporary VLEs is therefore better understood as an interaction among learners, educators, pedagogical processes, and intelligent technologies rather than as a process of technological adaptation alone.

NEED AND SIGNIFICANCE OF THE STUDY

The increasing use of AI in VLEs has created new opportunities for personalization, but it has also exposed limitations in predominantly technology-centered approaches. The literature addresses personalized learning, adaptive technologies, learning analytics, AI-supported education, self-regulated learning, and student engagement from different perspectives; however, these strands are frequently examined separately. A conceptual gap therefore remains in explaining **how technological intelligence, learner agency, pedagogical guidance, multidimensional engagement, and ethical responsibility interact within contemporary VLEs.**

This gap is further expanded with the arrival of GenAI. Previous personalization systems were based on learner profiles, rules, and content selection mechanisms, whereas generative systems can provide responses on-the-fly and enable iterative, conversational interactions. Such interaction enables opportunities for more dialogic forms of learning and personalization; but currency of conversation in itself may not afford meaningful learner agency. Empirical research on learner-ChatGPT interactions points to the possibility that students' interactions with conversational AI may also be relatively shallow and that they may manifest similarly limited agentic orientations in their interactions with these particular interactive systems (Lee et al., 2025). In the same way, studies of students' learning strategies with GenAI also highlight that agency is demonstrated in the way students actively interrogate, contest, modify and think about AI-mediated learning and not just in the utilisation of the technology (Yang et al., 2024). Hence the pedagogical importance of conversational personalization depends on the ability not only of the system to create a responsive



dialogue but also of learners to question, negotiate, assess, and affect the learning trajectory. The question of whether technology can adapt learning to individual students, so that students can adapt themselves to systems may be too straightforward, yet instead of shying away from the issue, the literature should also inquire into the possibility of learners developing, negotiating, and shaping, just like the technology and intelligent systems that mediate personalisation.

The need for such an integrated perspective is further reinforced by the ethical and inclusive challenges associated with AI-enhanced VLEs. Increasing dependence on learner data raises concerns regarding privacy, transparency, data governance, algorithmic bias, and accountability, while unequal access to devices, connectivity, accessibility features, and digital competencies may affect who benefits from intelligent personalization (Hamdan et al., 2015; Hashim et al., 2022; Gottschalk & Weise, 2023). Consequently, technological innovation must be considered alongside pedagogical quality, learner autonomy, inclusion, digital well-being, and sustainability.

Against this background, the present paper aims **to critically synthesize the evolving literature on personalized learning and student engagement in VLEs, examine how contemporary intelligent technologies interact with multidimensional student engagement and learner agency, and propose an integrative conceptual framework for human-centered intelligent personalization.**

The study is significant in three respects. First, it brings together technological and pedagogical perspectives that are often treated independently. Second, it places learner agency and the four dimensions of engagement, behavioral, cognitive, emotional, and agentic, within the discussion of AI-enhanced personalization. Third, it proposes the **Human-Centered Intelligent Engagement Framework (HCIEF)**, integrating technological intelligence, learner agency and self-regulation, human-centered pedagogy, multidimensional engagement, and ethical and sustainable foundations. The framework is intended as a theoretically informed proposition that can guide the design and critical evaluation of intelligent VLEs and provide a basis for future empirical validation.

RESEARCH QUESTIONS

The paper is guided by the following research questions:

- **RQ1.** How has the evolution of virtual learning environments and emerging AI technologies transformed the possibilities for personalized learning?
- **RQ2.** How can AI-enhanced personalization influence the behavioral, cognitive, emotional, and agentic dimensions of student engagement?
- **RQ3.** What roles do learner agency, self-regulated learning, and human-centered pedagogy play in shaping meaningful intelligent personalization?
- **RQ4.** What ethical, inclusive, and sustainable considerations should guide the design and implementation of AI-enhanced personalized VLEs?
- **RQ5.** How can the identified technological, learner-centered, pedagogical, engagement-related, and ethical dimensions be integrated into a human-centered conceptual framework for intelligent personalization?



LITERATURE REVIEW

Conceptualizing Personalized Learning in Virtual Learning Environments

Personalized learning represents a shift from standardized instructional provision towards learning experiences that respond to differences in learners' characteristics, needs, prior knowledge, progress, interests, preferences, goals, and learning circumstances. Rather than assuming that all learners should encounter identical content, instructional strategies, learning pathways, and pacing, personalization seeks to provide appropriate levels of challenge, support, flexibility, choice, and feedback in response to learner variability (Basham et al., 2016; Walkington & Bernacki, 2020). This orientation is particularly significant in digitally mediated learning because technology can expand the range of resources, pathways, interactions, and forms of feedback available to learners. Nevertheless, personalized learning is more appropriately understood as a **pedagogical orientation than as a technological intervention**. The presence of adaptive technologies does not, in itself, establish that learning has become personalized; educational personalization depends on the alignment among learner needs, pedagogical purposes, instructional design, assessment, teacher judgement, and opportunities for meaningful learner participation.

The learner-centered character of personalization is closely associated with learner agency and self-regulation. Research on personalized learning has similarly emphasized the mutuality of teacher and student agency in shaping personalized learning processes (Deed et al., 2014). Meaningful personalization provides learners with opportunities to exercise some degree of control over what, how, and when they learn, while also enabling them to monitor their progress, select strategies, reflect on their learning, and respond to feedback. This emphasis distinguishes personalization from simple differentiation performed exclusively by an instructional system or teacher. Personal Learning Environments (PLEs) have been influential in articulating this learner-centered orientation because they emphasize learners' capacity to select, organize, connect, and manage digital resources and learning activities (Ivanova & Chatti, 2011; Kop, 2010). Research on PLE integration similarly highlights the potential of digitally mediated environments to provide learners with greater flexibility and opportunities to organize learning according to their individual requirements (Nuraini & Shahbodini, 2015). In this sense, personalization involves not only adapting learning to learners but also enabling learners to participate actively in shaping their own learning environments.

This distinction is important because personalization can take substantially different forms. An environment may personalize learning by recommending resources, adjusting difficulty, sequencing activities, or providing individualized feedback on the basis of learner data. Such forms of adaptation can increase responsiveness, but they may still position the learner primarily as the recipient of decisions made by a teacher, algorithm, or platform. A more learner-centered conception gives learners opportunities to influence these processes by expressing preferences, selecting resources, modifying pathways, setting goals, and responding to recommendations. Ali et al. (2015), in examining personalization within learning environments, further illustrate the significance of interaction and recommendation mechanisms in supporting individualized learning. Taken together, this literature suggests that personalization should be evaluated not merely according to the extent to which a



system differentiates learning experiences, but according to the extent to which differentiation supports learner participation, control, and meaningful engagement with learning.

The development of PLEs also provides an important conceptual background for understanding contemporary personalized Virtual Learning Environments (VLEs). Whereas VLEs have traditionally been institutionally structured spaces in which content, communication, assessment, learning activities, and learner support are organized, PLEs emphasize the learner's role in assembling and managing digital resources and connections. These orientations are not necessarily contradictory. Contemporary VLEs increasingly incorporate features associated with PLEs, including learner choice, adaptive pathways, external resources, collaborative spaces, and mechanisms for monitoring learning. The resulting convergence expands the possibilities for personalization while also raising questions about who controls the personalization process. A system may provide extensive adaptive functionality while retaining highly centralized control over the learner's pathway; conversely, an environment may provide substantial learner choice without providing sufficient pedagogical guidance. Personalization therefore involves a continuing negotiation between **system responsiveness, learner agency, and pedagogical direction**.

Within VLEs, this negotiation is supported by the capacity of digital environments to integrate instructional content, communication, assessment, learning activities, feedback, and interaction while simultaneously generating information about learners' activities and progress (Verpoorten et al., 2009; Klašnja-Milićević et al., 2020). In VLEs, learning analytics can be used to build evidence of participation and performance patterns by recording indicators such as log-ins, time-on-task, access to resources, activity in discussions, and completion of tasks. Nevertheless, such digital traces mainly offer proof of visible actions in itself and they should not be taken as definitive measures of student engagement. A recent systematic review of learning analytics research revealed that engagement is often operationalised on the basis of observable activities such as clicks and duration of activities, with much less consideration being given to cognitive and affective components of engagement (Bergdahl et al., 2024). In a similar vein, studies on online learning analytics show that LMS log files allow for the tracking of behavioural participation but do not fully capture learners' cognitive and emotional participation (Caspari-Sadeghi, 2022; Henrie et al., 2018). Observable digital activity cannot, by itself, provide the depth of cognitive engagement, lived emotional experience, intentions, or learner agency (Kizilcec et al., 2017). Adaptation based on data should not therefore be equated with learner-centred personalization, in and of itself. Instead, digital traces need to be correlated with contextual, pedagogical, and learner-generated data to obtain a fuller picture of engagement.

The literature also shows that personalization is to be understood in relation with learner differences and inclusion. For instance, Universal Design for learning (UDL) stresses the importance of engagement, representation and expression to address learner differences (Basham et al., 2016). Yet, including personalization in the curriculum design does not automatically imply equal learning opportunities. Disparities in device and internet access, digital skills, and the quality of tech support may affect students' ability to engage in and learn from digitally mediated education (van de Werfhorst et al., 2022; Luo & Liu, 2025). This worry becomes particularly salient as more sophisticated AI-enabled systems provide differentiated types of support and personalization.



From this vantage point personalization should not be a filtering process by means of which those who have more access to technology or have more advanced digital literacy skills are able to gain substantially greater benefits, while the rest remain marginally disadvantaged. Instead, personalization becomes pedagogically meaningful when it enables an increase in venture- and learning-relevant opportunities for participation amongst a diverse range of learners. This also implies that the “quality” of personalization cannot be evaluated by the accuracy by which a system predicts a user's individual traits. Its educational quality rests on whether such predictions in turn give rise to feasible, pedagogically sound and fair opportunities to learn.

There is a further question about how personalisation and pedagogical judgement relate to one another. Although technological systems are increasingly capable of detecting patterns in learners' behaviour and suggesting resources or pathways, understanding if a specific adaptation is educationally valid requires an interpretation of the learner, the learning goal, the educational context, and the macro educational purpose. Recent studies of teachers' engagement with algorithmic advice also show that, while teachers do consult algorithmic advice, they equally continue to rely on their own professional judgement when making decisions about pedagogy (Henderson et al., 2026). Personalized learning thus remains a relational practice that connects learners, educators, technologies, learning resources, assessment mechanisms, and institutional frameworks. The teacher may not be displaced by personalisation but instead the role may shift toward interpreting data about learners, crafting meaningful learning experiences, feedbacking, helping learners make decisions and setting appropriate limits on choice. In this respect, it is in line with the argument that learner agency and pedagogical guidance are best conceived as intertwined rather than polarised constructs.

The conceptual development of personalized learning consequently reveals a tension that becomes increasingly important as VLEs become more intelligent. On one hand, advances in digital technologies can make learning environments more responsive to individual differences and can provide forms of adaptation that would be difficult to achieve through standardized instruction alone. On the other hand, the increasing automation of personalization may create the impression that learning becomes learner-centered simply because content or pathways are algorithmically differentiated. The literature instead points towards a more demanding conception in which personalization involves **responsiveness, learner participation, pedagogical intentionality, and equitable access**. This distinction provides an essential foundation for examining student engagement: if personalization is intended to improve the quality of learners' experiences, its educational value must ultimately be considered in relation to how learners participate, think, feel, regulate, and exercise agency within the learning process.

Student Engagement as a Multidimensional Construct in Digital Learning

Student engagement has long been regarded as a central construct for understanding the quality of learners' participation in educational processes. However, engagement is not synonymous with attendance, task completion, or visible participation. The established literature conceptualizes engagement as a multidimensional construct encompassing behavioral, cognitive, and emotional



dimensions (Fredricks et al., 2004). **Behavioral engagement** concerns participation, effort, persistence, and involvement in learning activities; **cognitive engagement** concerns the quality and depth of learners' mental investment, including strategic learning, self-regulation, deep processing, and critical thinking; while **emotional engagement** encompasses interest, enjoyment, confidence, belonging, and learners' affective responses to learning. This multidimensional conceptualization is particularly relevant to personalized learning because adaptation can influence not only whether learners participate but also whether they perceive learning activities as relevant, experience appropriate challenge, and invest cognitively and emotionally in the learning process (Kim, 2012; Abedi et al., 2021).

The relevance of engagement becomes more pronounced in Virtual Learning Environments, where conventional indicators of participation can be readily captured through digital systems. Log-ins, time spent on a platform, number of resources accessed, discussion contributions, assignment submissions, and task completion provide visible evidence of learner activity. Yet such indicators provide only a partial account of engagement. A learner may spend considerable time within a VLE without engaging deeply with the learning material, while another may interact selectively but demonstrate substantial cognitive investment. Consequently, the increasing capacity of VLEs to record learner behaviour should not be mistaken for an equivalent capacity to measure the full quality of learner engagement. This distinction becomes particularly important as learning environments become increasingly data-driven and adaptive.

The limitations of behavioural indicators also highlight the importance of distinguishing **activity from meaningful engagement**. Personalized learning may increase the relevance of resources, adjust the level of challenge, provide flexible pacing, or offer timely feedback, thereby creating conditions that are conducive to participation and persistence. However, these adaptations do not necessarily result in deeper cognitive engagement or positive emotional experiences. Similarly, an increase in platform activity cannot by itself demonstrate that learners are developing conceptual understanding, employing effective learning strategies, experiencing a sense of belonging, or exercising control over their learning. The relationship between personalization and engagement is therefore contingent rather than automatic. The literature on engagement in digitally mediated learning reinforces the importance of considering the quality of learners' involvement rather than relying exclusively on observable participation (Gray & DiLoreto, 2016; Vendrell & Johnston, 2026).

Within personalized VLEs, cognitive engagement is especially important because personalization can potentially alter the depth and nature of learners' interaction with content. Adaptive systems may provide additional explanations, scaffold difficult concepts, recommend resources, adjust task complexity, or provide individualized feedback. Such functions can support learners in moving beyond passive reception towards strategic and deeper forms of learning. At the same time, excessive automation can produce the opposite effect if systems routinely supply answers, explanations, or pathways without requiring learners to interpret, question, evaluate, or construct knowledge. Personalized support can therefore facilitate cognitive engagement, but its effect depends on whether it **supports cognitive activity or substitutes for it**. This distinction becomes increasingly significant in AI-enhanced environments where systems can generate increasingly sophisticated responses to individual learner inputs.



Emotional engagement represents another dimension through which personalization may influence learners' experiences. Learning activities that are appropriately matched to learners' needs, interests, levels of readiness, and goals may increase perceived relevance and reduce experiences of inappropriate difficulty or disengagement. Kim (2012) and Abedi et al. (2021) provide a basis for considering the relationship between personalization and motivational or engagement-related outcomes. However, emotional engagement cannot be inferred solely from system responsiveness. A technically individualized environment may still fail to generate confidence, belonging, enjoyment, or sustained interest if learners perceive the interaction as impersonal, overly automated, intrusive, or disconnected from their educational and social context. Consequently, emotional engagement requires attention not only to adaptive functionality but also to the quality of the learner's relationship with the learning environment and the people involved in it.

For contemporary personalized and AI-enhanced environments, the three-dimensional conception of engagement is usefully extended through **agentic engagement**. Reeve and Tseng (2011) describe agentic engagement in terms of learners' proactive contribution to and influence over the learning process, including expressing preferences, communicating needs, asking questions, seeking clarification, and contributing to the shaping of learning experiences. This dimension is particularly significant for intelligent personalization because personalization can otherwise become a process in which decisions are made *about* learners without meaningful participation *by* learners. The distinction is consequential: an AI system may accurately infer a learner's needs and automatically modify content, while the learner remains largely passive in relation to the decisions governing the learning experience. Conversely, when learners can question recommendations, modify goals, request alternative explanations, select resources, and respond to AI-generated feedback, personalization becomes more participatory.

Agentic engagement therefore introduces an important dimension of **control and negotiation** into the conceptualization of personalized learning. It shifts attention from the question of whether an intelligent system can adapt learning to the learner towards whether the learner can participate in determining how learning is adapted. This distinction is particularly important in relation to learner agency and self-regulation. If an intelligent VLE continuously determines what a learner should study next, which resource should be consulted, what level of difficulty should be presented, and which strategy should be followed, the system may provide highly individualized instruction while simultaneously narrowing opportunities for learners to make decisions about their own learning. Personalization can consequently support agency, but it can also potentially displace it. This tension provides an important conceptual link between engagement and the subsequent discussion of learner agency and self-regulated learning.

The multidimensional nature of engagement also means that the four dimensions should not be treated as isolated outcomes. Behavioral, cognitive, emotional, and agentic engagement can interact dynamically within the learning process. For example, a learner who perceives a personalized activity as relevant may become more emotionally invested, participate more actively, employ greater cognitive effort, and subsequently communicate preferences or request additional support. Conversely, a learner who experiences irrelevant recommendations or excessive automation may exhibit reduced participation, weaker cognitive investment, negative affect, and limited willingness



to influence the learning process. Engagement is therefore better understood as an **interrelated and evolving process** rather than a set of independent indicators.

This interpretation has particular significance for AI-enhanced personalization. AI systems can increase the speed, scale, and granularity with which learning experiences are adapted, but their ability to generate or detect learner-related information does not establish that the resulting learning experience is engaging. The educational value of intelligent personalization depends on whether technological adaptation produces conditions under which learners participate meaningfully, invest cognitively, experience positive affect, and retain the capacity to influence their learning. Thus, the four-dimensional conceptualization adopted in this paper, **behavioral, cognitive, emotional, and agentic engagement**, provides a more comprehensive basis for evaluating personalized VLEs than measures based solely on observable digital activity. The inclusion of agentic engagement is particularly important because it connects engagement to the human-centered orientation that underpins the Human-Centered Intelligent Engagement Framework (HCIEF).

Personalization and Engagement as a Reciprocal Process

The relationship between personalized learning and student engagement should consequently not be conceptualized as a simple linear relationship in which personalization automatically produces engagement. Personalization can create conditions conducive to engagement by increasing relevance, providing appropriate challenge, supporting flexible pacing, offering timely feedback, and creating opportunities for learner choice (Kondratova et al., 2018). At the same time, learners' behaviours, choices, reflections, interactions, and feedback can provide information that enables further refinement of the learning experience. The relationship is therefore more appropriately conceptualized as **dynamic and reciprocal** rather than unidirectional, as presented in **Figure 1**:

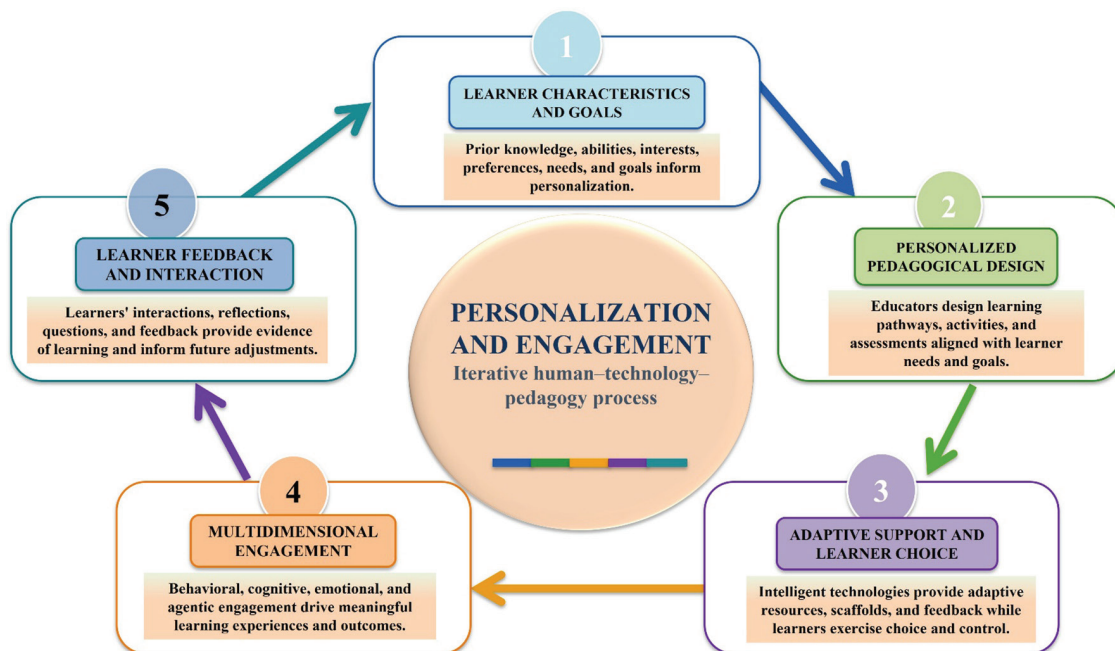


Figure 1. The Dynamic Cycle of Personalization and Engagement in Virtual Learning Environments



In the cycle, learner characteristics inform pedagogical design and adaptive support; personalized experiences facilitate engagement; and learners' interactions, choices, and feedback subsequently provide information for further personalization. This conceptualization moves beyond static matching between learner characteristics and predefined content. Personalization becomes an iterative process of **sensing, interpreting, adapting, engaging, and reflecting**, involving learners, educators, learning analytics, adaptive technologies, and increasingly generative AI.

The reciprocal model also adds an important qualification. While intelligent systems may be able to learn more and more patterns in learner behaviour and create adaptive responses, the decision of whether a specific adaptation is educationally appropriate cannot be based solely on an algorithmic prediction. The interpretation of learner behaviour must always be contextualized within learning objectives, the learning environment, pedagogical design, learner agency, and the overall goals of education. Therefore, engagement is not just something an intelligent system tries to optimize as an outcome. It can also be used to inform future pedagogical and technological adaptation when learners interact to communicate their needs, evaluate responses, adjust requests, and influence subsequent interactions. Recent work has conceptualized agency in the context of AI-supported learning as a reciprocal process where learners' inputs drive AI responses, which, in turn, drive learners' actions and choices (Dai et al., 2026). In the same way, empirical studies on learners' interactions with AI-generated feedback show that extended interaction can involve goal setting, evaluation, reflection and revision, and that learner activity can be part of an iterative process of learning and adaptation (Ma et al., 2026). Hence, in HCIEF, engagement is understood not only as an outcome of personalization but also as a means through which learner-generated data can facilitate subsequent adaptation, with learners and educators maintaining meaningful roles in interpreting and responding to that data.

From Conventional Personalization to Intelligent Personalization

The development of Virtual Learning Environments has involved a gradual transition from relatively structured platforms for content delivery and communication towards increasingly adaptive, data-informed, and interactive learning ecosystems. Early forms of personalization primarily relied on learner profiles, digital resources, and predefined adaptive pathways, through which content, sequencing, or difficulty could be adjusted according to identified learner characteristics or performance (Shin, 2018). Subsequent developments in learning analytics, adaptive learning systems, artificial intelligence (AI), recommendation technologies, and immersive environments have considerably expanded the capacity of VLEs to respond to learner behaviour, performance, preferences, and progress (Verpoorten et al., 2009; Zhang et al., 2020; Walkington & Bernacki, 2020). This progression has transformed personalization from relatively predetermined forms of differentiation towards increasingly dynamic processes in which learning environments can analyse information, generate responses, and modify learning experiences in real time.

A significant development in this trajectory has been the movement from **predefined adaptive systems towards intelligent personalization**. Earlier adaptive systems generally operated through predetermined rules that adjusted content, sequencing, or task difficulty on



the basis of learner characteristics and performance (Colace et al., 2014). Although such systems represented an important departure from standardized instruction, their capacity for adaptation remained constrained by the parameters established during system design. The incorporation of AI has expanded these possibilities by enabling systems to analyse larger and more complex sets of learner information, identify patterns, generate predictions, recommend resources, support individualized pathways, and provide increasingly responsive feedback (Sharma et al., 2025). Recent research identifies adaptive learning, individualized content, learner prediction, and real-time feedback among the expanding applications of AI in education (Hashim et al., 2022; Ayeni et al., 2024; Juyal et al., 2025). Consequently, personalization is increasingly becoming a process of continuous adaptation rather than a fixed allocation of learners to predefined pathways.

Learning analytics constitutes an important evidential layer in this transformation. By examining patterns of participation, progress, performance, interaction, and other forms of digital activity, learning analytics can provide information for recommendations, interventions, and instructional decisions (Klašnja-Milićević et al., 2020). Its contribution is particularly significant because intelligent personalization depends on the capacity of a learning environment to interpret information about learners and translate that information into appropriate responses. However, the increasing datafication of learning also exposes a fundamental limitation. Digital traces represent **observable activity rather than engagement in its entirety**. Login frequency, time-on-task, resource access, discussion activity, and task completion can provide evidence of behavioral participation, but they cannot independently establish cognitive investment, emotional involvement, or learner agency. Consequently, learning analytics should function as an evidential resource for pedagogical interpretation rather than as a substitute for such interpretation. This distinction is consistent with the multidimensional conceptualization of engagement established earlier in this review.

The emergence of conversational AI has further changed the interactional possibilities of personalized VLEs. Chatbots and conversational systems can provide immediate assistance, clarification, individualized feedback, and support for self-directed learning (Baskara, 2023). Unlike conventional adaptive systems that primarily select or sequence existing resources, conversational systems enable learners to interact with learning technologies through more flexible forms of dialogue. This development has been accompanied by the rapid emergence of generative AI and large language models, which can generate explanations, examples, questions, summaries, feedback, and learning resources in response to individual learner inputs (Baidoo-Anu & Ansah, 2023; Beale, 2025; Lee & Moore, 2024; Ivanova & Terzieva, 2026; Samala et al., 2025). The growing use of such systems has consequently expanded the scope of personalization from the **selection and sequencing of existing learning materials to the dynamic generation and negotiation of learning content**.

The educational implications of this transition, however, require careful qualification. A system may generate a response specifically tailored to an individual learner without necessarily producing a genuinely personalized learning experience. An individualized explanation can provide immediate assistance, but it may have limited educational value if it discourages learners from questioning, reflecting, evaluating, or constructing knowledge independently. Similarly, automated feedback may be efficient and responsive while failing to address contextual or pedagogical considerations



that an educator might recognize. Research examining generative AI therefore points not only to its expanding educational applications but also to challenges concerning accuracy, pedagogical integration, learner dependence, and responsible use (Baidoo-Anu & Ansah, 2023; Samala et al., 2025). The critical issue is consequently not whether AI can produce individualized responses, but **how those responses are incorporated into learning processes that preserve cognitive engagement, learner agency, and pedagogical purpose.**

The distinction between technological personalization and educational personalization becomes particularly important with the increasing use of large language models. Their capacity to respond conversationally to learner inputs creates possibilities for iterative questioning, alternative explanations, differentiated examples, and adaptive feedback. These functions can potentially make learning more responsive to individual needs and provide forms of support that are difficult to deliver consistently through conventional instruction. At the same time, the apparent flexibility of conversational interaction can obscure the distinction between **responsive technology and pedagogically responsive learning.** The generation of a plausible or personalized response does not guarantee conceptual accuracy, appropriate difficulty, meaningful challenge, or alignment with the learner's educational objectives. Accordingly, the value of generative AI depends on the pedagogical context in which it is deployed and on the extent to which learners and educators remain capable of evaluating and directing its outputs.

Another significant development is the expansion of personalization from the adaptation of content and pace towards the adaptation of learning experiences through immersive technologies. Virtual reality, augmented reality, and related immersive technologies can provide simulations, experiential environments, and interactive activities that support differentiated and context-sensitive learning experiences (Marougkas et al., 2021; Shin, 2018; Wang et al., 2025). Such technologies may be particularly useful when learning requires experiential engagement, visualization, spatial interaction, or simulated environments that are difficult to reproduce through conventional digital resources. Nevertheless, immersion should not be treated as synonymous with pedagogical effectiveness. Its educational contribution depends on alignment with learning objectives, instructional design, accessibility, infrastructure, learner readiness, and the nature of the learning task. Technological sophistication alone cannot establish that an immersive experience is educationally meaningful.

Taken together, the literature suggests a broad technological trajectory:

**Digital Content Delivery → Adaptive Personalization → Learning Analytics →
AI-Supported Personalization → Conversational and Generative Personalization →
Increasingly Interactive Learning Ecosystems**

This progression represents a substantial expansion in what VLEs can technically accomplish. Contemporary systems can increasingly **sense learner activity, analyse patterns, recommend pathways, adapt resources, generate content, provide feedback, and interact with learners in real time.** Yet the expansion of technological capability also makes it increasingly important to distinguish between what a system *can do* and what it *should do pedagogically.* Technological



intelligence may increase the speed, scale, and granularity of personalization, but it does not automatically establish meaningful learning.

This distinction is central to the present review because the increasing intelligence of VLEs changes the nature of the relationship between technology and learner engagement. When adaptive systems merely adjust content or difficulty, personalization is principally a matter of instructional responsiveness. When AI systems begin to generate explanations, recommend strategies, interpret learner behaviour, and participate in conversational interactions, personalization becomes an increasingly complex process involving **technology, cognition, agency, pedagogy, and human judgement**. The question consequently shifts from whether VLEs can personalize learning to whether increasingly intelligent personalization can contribute to **meaningful, sustained, and multidimensional student engagement without displacing the learner's own participation in the learning process**.

This question provides the necessary foundation for examining AI-enhanced personalization specifically through the four dimensions of engagement established earlier, behavioral, cognitive, emotional, and agentic. It also introduces the central tension that runs throughout the subsequent literature: **the same technologies that can increase responsiveness and individualized support can also increase automation and potentially reduce learner choice, cognitive effort, or human interaction**. The next section therefore examines how AI-enhanced personalization may influence each dimension of student engagement and under what conditions such influence can remain educationally meaningful.

AI-Enhanced Personalization and Multidimensional Student Engagement

The increasing intelligence of Virtual Learning Environments has expanded the possibilities for connecting personalization with student engagement. AI-enabled systems can analyse learner information, identify patterns of performance and participation, adapt content and difficulty, recommend resources, provide individualized feedback, and support increasingly interactive forms of learning. These capabilities create opportunities to move beyond static personalization towards learning experiences that respond continuously to learners' changing needs and behaviours (Hashim et al., 2022; Ayeni et al., 2024; Juyal et al., 2025). However, the relationship between AI-enhanced personalization and engagement should not be understood as automatic or deterministic. The educational value of intelligent personalization depends on whether technological responsiveness contributes to meaningful participation, cognitive investment, positive emotional experiences, and learner agency.

Behavioral Engagement

Behavioral engagement is a learner's active efforts, sustained persistence and concentration in learning activities. In VLEs, AI-enhanced personalization can foster these processes on the level of course delivery by means of adaptive sequencing, differentiated resources, individualized task difficulty, recommendations, and timely feedback. Adaptive systems that better tailor learning



activities to the immediate goals and skills of learners may therefore also lower levels of participation barriers and promote ongoing participation in learning (Walkington & Bernacki, 2020; Hashim et al., 2022). Recent theoretical and empirical integration suggests that this may be possible. A systematic review and meta-analysis of 17 empirical research articles, which included 1735 students in total, revealed that ChatGPT-facilitated learning resulted in a medium positive effect on overall student engagement and a medium positive effect on behavioural engagement in particular when compared to non-ChatGPT learning (Heung & Chiu, 2025). Yet the result of AI-supported learning on behavioral engagement exhibited high heterogeneity, which implied that the effect of AI-supported learning is context specific. A more comprehensive systematic review of 73 peer-reviewed articles also revealed that similar AI tools including chatbots, adaptive systems (AS) and predictive analytics were the most successful in promoting engagement in interactive pedagogy, differentiated instruction and scaffolded feedback (Long et al., 2026). These results highlight the essential role for pedagogical mediation in transforming technological affordances into meaningful participation.

The connection, however, needs to be critically qualified. A rise in platform activity should not be taken as a sign of increased engagement. An AI system can also lead learners to engage with a platform more often, but that increase in frequency may not translate into a corresponding increase in quality or intention of engagement. Recommendations can motivate learners to go through more resources without guaranteeing they do so in a meaningful way, while automated prompts can persuade learners to finish more tasks without necessarily making them more persistent, committed, or intrinsically involved. Behavioral engagement, then, might be believed to be more than digital activity that can be tracked. Its educational importance is a function of the quality and purpose of the participation of the learners. From a human-centered perspective, AI should thus be employed to foster meaningful participation and persistence and not merely to enhance platform activity per se.

Cognitive Engagement

Cognitive engagement refers to the extent and quality of learners' mental effort in learning, including strategic processing, reflection, problem solving, critical thinking, and self-regulation. AI-enhanced personalization can help support these processes through the use of differentiated resources, adaptive scaffolding, targeted explanations, appropriately challenging activities, and individualized feedback (Walkington & Bernacki, 2020; Hashim et al., 2022). Generative AI can also facilitate the iterative learning process by allowing learners to ask for alternative explanations, to generate examples, to test concepts, to receive graduated assistance, and to discuss problems. Recent empirical evidence supports this potential. A systematic review and meta-analysis of learning supported by ChatGPT showed a large positive effect on cognitive engagement, compared with non-ChatGPT learning, but the review also noted the possible risks of over-reliance and disengagement (Heung & Chiu, 2025). Likewise, a meta-analysis of 57 studies and 97 effect estimates showed positive effects of GenAI on higher-order thinking, with no statistically significant effect on metacognition (Chen & Cheung, 2025). The results highlight the potential of AI to provide cognitive scaffolding and to promote higher-level thinking, but cognitive support should not be automatically equated with the development of learners' independent regulatory abilities. The evidence on AI-supported self-



regulated learning also shows that educational chatbots and other AI applications can help learners with strategy use, monitoring, feedback, and some elements of reflection, although the support is not consistently comprehensive throughout the self-regulatory cycle and the effects on learning performance are mixed across studies (Guan et al., 2025; Lan & Zhou, 2025). The educational value of intelligent personalization is therefore a function of whether directing assistance towards learners serves to empower their own interpreting, questioning, evaluating, problem solving, and reflecting processes. If AI regularly delivers finished solutions, or eliminates some of the cognitive labor, the very technological affordance that makes cognitive support possible may have the unintended consequence of diminishing opportunities for learners to build knowledge on their own. In this sense, “real” personalization should serve as a cognitive scaffolding, extending learning capabilities, and not as an automation that gradually replaces learners’ cognitive and metacognitive activities.

For learners to use AI mainly to get completed answers, to generate assignments, or to skip the more challenging steps of reasoning, the efficiency of technology may come at the cost of less cognitive processing. Evidence from learning contexts involving AI support shows that students may become dependent on AI assistance instead of learning from the assistance itself, which raises questions about how much students still think for themselves and put in cognitive effort (Darvishi et al., 2024). Recent experimental evidence has also raised red flags about the long-term learning outcomes of unconstrained reliance on generative AI, with one randomized controlled trial finding lower delayed knowledge retention among students who used ChatGPT as a study tool compared with students who used traditional learning techniques (Barcaui, 2025). The implication is that the educational value of AI depends not just on whether it reduces cognitive effort, but on how that reduction is orchestrated within the learning process. Cognitive offloading can help facilitate higher-order activity when directed appropriately, but it can become a concern when the external technological aid replaces, rather than complements, learners’ cognitive engagement (Iqbal et al., 2025). Therefore, human-centered intelligent engagement requires AI to prompt thinking, questioning, reflection, and problem solving, not just to provide completed answers.

Emotional Engagement

Emotional engagement includes what children like to do, what they enjoy, what motivates them, how confident they feel, if they feel included, and whether or not they think the things they are learning are relevant. Personalization may contribute to these aspects when students participate in experiences that challenge them as learners and are aligned with their needs and interests. Adaptive pacing, individualized feedback, interactive environments, and conversational support may lead to enhancing the factors of relevance, enjoyment, confidence, and willingness to communicate (Kim, 2012; Abedi et al., 2021; Marougkas et al., 2021). Emerging empirical evidence synthesis support the potential for this: a systematic review and meta-analysis of 17 studies (involving 1,735 students) reported a medium effect on student engagement via ChatGPT-supported learning, with favorable effects on behavioral, cognitive, and emotional engagement, but also observed large heterogeneity across studies and a potential risk of over-reliance (Heung & Chiu, 2025). Similar to the data on efficacy, findings from broader GenAI research demonstrate positive effects in terms of affective-motivational outcomes and educational



achievement, dependent on learner characteristics, instruction activity, duration, and contextual constraints (Chen & Cheung, 2025). These results demonstrate that AI-enabled personalization can enhance engagement and motivation, but these outcomes cannot be solely attributed to technological adaptation. Rather, improvements in engagement are better seen as resulting from the integration of adaptive, individualized technological support into suitable pedagogical approaches and active learner involvement. Processes of emotional engagement are also sparked by relational exchanges that could never be algorithmically mediated. Teacher presence, support, acknowledgement, substantive interaction, and community of learning therefore continue to be significant aspects of quality learning experiences (Gray & DiLoreto, 2016; Li et al., 2026). Intelligent technologies may be integrated with relational pedagogy, but should never be presented as its replacements.

Agentic Engagement

Agentic engagement is particularly significant for AI-enhanced personalized learning because it concerns learners' proactive contribution to and influence over the learning process. It includes expressing preferences, communicating needs, asking questions, seeking clarification, suggesting modifications, and participating in the shaping of learning experiences (Reeve & Tseng, 2011). Unlike behavioral engagement, which can be observed through participation, agentic engagement concerns the extent to which learners actively influence the conditions under which they learn. AI-enhanced VLEs create new possibilities for such engagement. Learners can negotiate learning goals, request alternative explanations, question recommendations, select resources, provide feedback, and modify interactions with intelligent systems. Generative AI is particularly significant because it permits learning interactions to take place through dialogue rather than exclusively through predetermined pathways (Kim et al., 2026). Such dialogue can provide learners with opportunities to articulate their needs and exercise greater control over the learning process.

However, this potential is conditional. If intelligent systems become overly prescriptive and increasingly determine learning pathways on behalf of learners, personalization may paradoxically reduce agency. An environment may therefore be highly personalized while remaining insufficiently agentic if learners have little opportunity to understand, question, modify, or reject the decisions made on their behalf. This establishes an important distinction between **personalization for learners and personalization with learners**. In the former, the system adapts learning to inferred learner characteristics; in the latter, learners actively participate in shaping the adaptation process. Agentic engagement consequently provides a particularly important criterion for evaluating intelligent personalization: the question is not simply whether the system adapts to the learner, but whether the learner can meaningfully influence how the environment adapts.

Self-Regulated Learning (SRL) as a Cross-Cutting Mechanism

Self-regulated learning provides an important mechanism connecting intelligent personalization with the different dimensions of engagement. Goal setting, planning, monitoring, strategy selection, regulation of effort, and reflection are especially significant in VLEs because digitally mediated



learning often requires learners to assume greater responsibility for managing their own learning. AI and learning analytics can support these processes by providing progress information, reminders, personalized recommendations, formative feedback, and prompts for reflection (Hashim et al., 2022; Tur et al., 2024). Recent reviews show that AI-guided tools, especially educational chatbots, can support a number of SRL processes, including resource identification, strategy use, monitoring, and feedback, although the support is less consistently developed for goal setting, planning, reflection, and adaptation of future learning (Guan et al., 2025; Lan & Zhou, 2025). Empirical evidence also shows that structured self-regulation scaffolding provided by chatbots can enhance learning-related outcomes, suggesting that AI can serve as a scaffold for, but not a replacement of, learners' regulatory processes (Tsai et al., 2025).

Conversely, the growing power of intelligent systems to guide learning presents a key tension between supporting self-regulation and externalizing regulatory decisions. As an AI system takes an ever-increasing role in prescribing what learners should learn, what resources they should use, or how they should respond when they struggle, there is a danger that learners will come to depend on external technological regulation instead of gradually developing their own ability to make and evaluate such choices (Darvishi et al., 2024; Risko & Gilbert, 2016). The question, then, is not whether AI should support regulation, but how regulation is structured. Intelligent personalization is of educational value if the information, scaffolding, feedback, and meaningful choices provided by AI enhance the learner's ability to regulate his/her learning and do not replace that ability. This perspective aligns with findings that artificial intelligence (AI)-supported monitoring and guidance can enhance certain aspects of self-regulated learning when situated in intentional pedagogical design (Lee et al., 2025; van Jaarsveld et al., 2025). Therefore, learners who can set goals, track progress, assess recommendations, and adjust their learning paths are not just being handed personalized instruction; they are part of the personalization process itself.

Synthesis: From Intelligent Adaptation to Intelligent Engagement

The literature therefore indicates that the relationship between AI-enhanced personalization and student engagement is **conditional rather than deterministic**. Intelligent technologies can facilitate participation, cognitive support, motivation, reflection, self-regulation, and learner agency, but these possibilities depend upon pedagogical alignment, teacher involvement, learner autonomy, and responsible technological design. The effectiveness of intelligent personalization consequently cannot be assessed solely by technological performance or by the quantity of learner data processed by a system.

A central tension cuts across the four dimensions of engagement. The same technology that increases responsiveness can also increase automation. Adaptive recommendations may facilitate participation while reducing learner choice; AI-generated answers may increase efficiency while reducing cognitive effort; and affective analytics may enable more responsive support while simultaneously introducing concerns about privacy, consent, transparency, and learner autonomy. Recent systematic evidence suggests that affective computing can be used to identify learning-centred affective states such as engagement, confusion and frustration, which can inform more



adaptive educational support, but also finds that relevant ethical issues are still not adequately addressed and that privacy is a major concern when exploring these issues (Salloum et al., 2025; Shingjergji et al., 2026). Affective computing research in education also highlights the need for safeguards against the unauthorized collection, over-monitoring, and intrusive observation of students' emotional data (Salloum et al., 2025). Thus, affective responsiveness should not be considered an unmitigated good in education. In a human-centred approach, the application of affective analytics should be explicit, proportionate, consent-based, and subject to meaningful learner and educator oversight.

A related question is whether algorithmic personalization is fair for different groups of learners. While AI-based systems could leverage data on learners to provide personalized suggestions, personalization does not necessarily imply equal treatment. Educational algorithms can mirror or magnify biases in training data, selected features, or decision rules, leading to systematically different results for certain groups of learners. A systematic review on algorithmic fairness in education reported similar fairness and bias-related issues in applications such as student performance prediction, dropout prediction, classification, and recommender systems, discussing that the evaluation of fairness of input data and the fairness of algorithmic outcomes are critical (Idowu, 2024). In line, studies of human-centred learning analytics and AI in education have raised algorithmic bias and discrimination as well as transparency, human control, privacy, and agency (Alfredo et al., 2024). Hence, from a human-centered view, the quality of personalization cannot be judged by predictive accuracy or the degree of individualization alone. However, it should also be judged by its fairness, transparency, and inclusiveness and its impact on learners. This means that human supervision and stakeholder engagement should continue to be central to the development, assessment, and continuous management of intelligent personalization systems.

The synthesis also indicates that the four dimensions of engagement should not be treated as independent outcomes. Behavioral participation can provide information that informs adaptation; cognitive engagement can influence subsequent learning recommendations; emotional responses can affect persistence and participation; and agentic contributions can directly modify the learning experience. Self-regulated learning operates across these dimensions by enabling learners to set goals, monitor progress, evaluate feedback, and exercise control over their learning. Intelligent personalization is therefore better conceptualized as a **dynamic interaction among technology, learner activity, pedagogy, and feedback** rather than as a one-way technological process.

METHODOLOGY

Research Design

This study adopted a **structured critical and thematic review approach combined with conceptual framework development** to examine the evolving relationship among personalized learning, Virtual Learning Environments (VLEs), artificial intelligence (AI), learner agency, self-regulated learning, human-centered pedagogy, and multidimensional student engagement. The review was designed to synthesize and critically interpret relevant theoretical, empirical, and review



literature published between **2009 and 2026**, thereby capturing both foundational developments in personalized and virtual learning and recent advances associated with learning analytics, adaptive technologies, conversational AI, and generative AI.

The study did not involve primary data collection from human participants. Published scholarly literature constituted the principal evidence base. The literature synthesis was subsequently used to identify recurring concepts, relationships, complementarities, and tensions across the technological, learner-centered, pedagogical, engagement-related, and ethical dimensions of intelligent personalization. These findings informed the development of the **Human-Centered Intelligent Engagement Framework (HCIEF)**. The framework is presented as a theoretically informed conceptual proposition rather than an empirically validated causal model.

Literature Search Strategy

Relevant literature to personalized learning, VLEs, AI-enhanced education, student engagement, learner agency, self-regulated learning, pedagogical design, learning analytics, and the ethical and inclusive dimensions of intelligent educational technologies was identified through a **structured literature search** across a number of scholarly databases and academic search platforms. Scopus, Web of Science, ScienceDirect, SpringerLink, ERIC, Google Scholar, and Crossref were included in the search. The search strategy was based on a combination of keywords and Boolean operators corresponding to the main concepts of the study.

The key search terms included "personalized learning," "personalised learning," "virtual learning environment," "VLE," "artificial intelligence," "AI in education," "generative AI," "adaptive learning," "learning analytics," "student engagement," "learner engagement," "learner agency," "self-regulated learning," "human-centered pedagogy," "intelligent personalization," "personalized feedback," "educational chatbot," "conversational AI," "algorithmic bias," "privacy," "digital equity," "accessibility," and "digital well-being." These terms were then variously combined according to the search capabilities and indexing practices of individual databases. Representative search combinations included:

- "personalized learning" AND "virtual learning environments"
- "personalized learning" AND "student engagement"
- "artificial intelligence" AND "personalized learning" AND engagement
- "AI in education" AND "learner agency"
- "adaptive learning" AND "self-regulated learning"
- "learning analytics" AND "student engagement"
- "generative AI" AND "personalized learning"
- "conversational AI" AND "learner engagement"
- "AI feedback" AND "self-regulated learning"
- "AI" AND "human-centered pedagogy"
- "AI-enhanced learning" AND privacy AND equity
- "intelligent personalization" AND "learner agency"



The search was limited to literature published from **2009 through 2026**. The starting point of 2009 was selected to capture foundational scholarship on personalization in virtual learning environments and related learner-centered digital learning developments, while extending the search through 2026 enabled consideration of contemporary developments in AI-enhanced and generative-AI-supported learning.

Literature Identification and Selection Flow

To enhance transparency in reporting the literature identification and selection process, a PRISMA-style flow diagram was developed to visually summarize the search sources, search scope, screening process, application of inclusion and exclusion criteria, and the final body of literature considered for thematic synthesis and conceptual framework development (**Figure 2**).

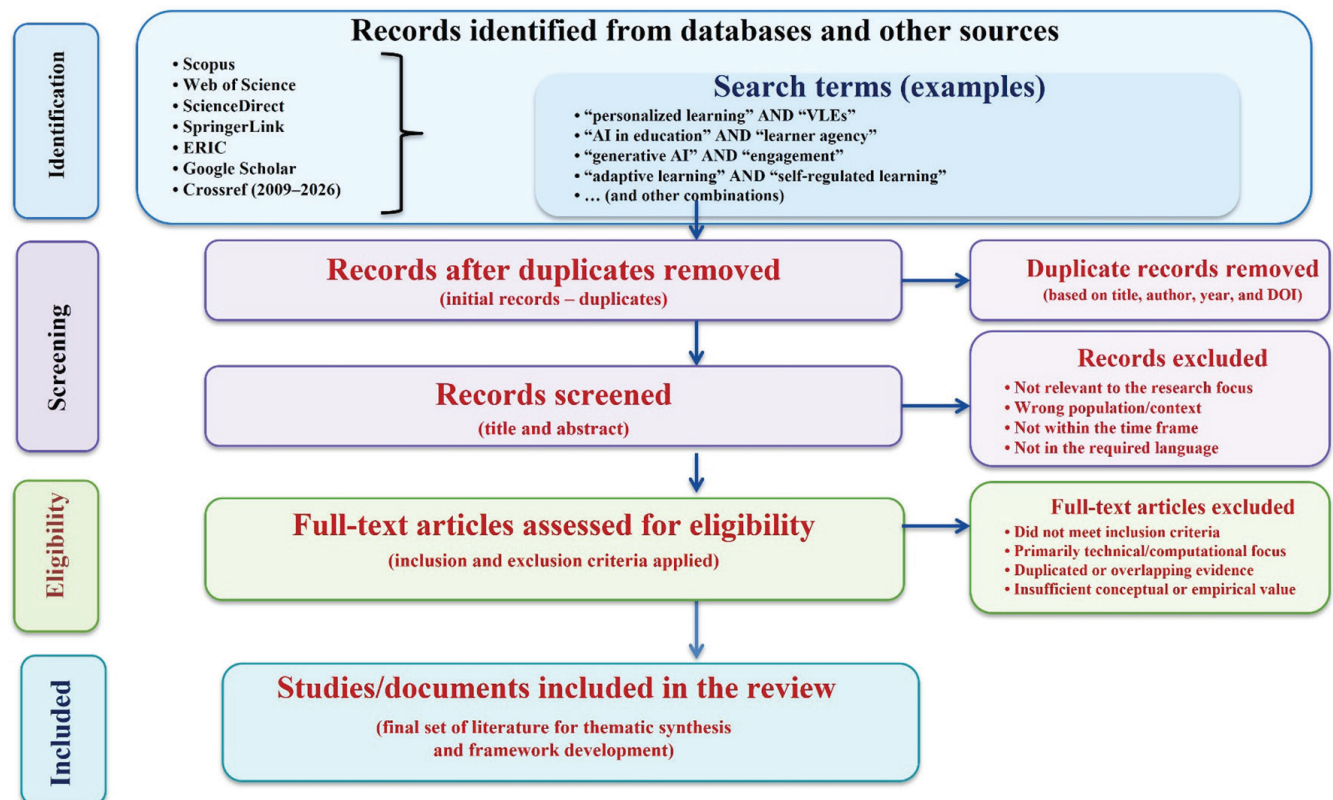


Figure 2. PRISMA-Style Flow Diagram of the Literature Identification and Selection Process

The flow diagram is presented in a PRISMA-style format as a transparency and reporting aid. The present study adopts a structured critical and thematic review approach combined with conceptual framework development and is not intended to constitute a formal systematic review or a PRISMA 2020-compliant systematic review.



Inclusion and Exclusion Criteria

The selection of literature was based on the conceptual and substantive relevance to the research focus and the proposed framework. The review considered sources addressing any of the following topics: (a) personalized/adaptive learning, (2) VLEs, personal learning environments, or digitally mediated learning ecosystems; (c) AI and intelligent technology-based education; (d) learning analytics, recommendation systems, adaptive technologies, conversational agents, or generative AI; (e) behavioural, cognitive, emotional, or agentic aspects of student engagement; (f) learner agency, autonomy, or self-regulated learning; (g) the role of teachers in technology-mediated personalized learning; and (h) ethical, inclusive, sustainable, privacy, equity, accessibility, transparency, or digital-well-being dimensions related to intelligent learning environments.

Both pioneering and current academic literature were considered. Foundational theoretical and conceptual literature was retained where it offered salient definitions, models or theoretical underpinnings for personalization, engagement, learner agency, or self-regulated learning. Recent empirical studies, systematic reviews, meta-analyses, and conceptual articles were considered where relevant to contemporary AI-enhanced learning and generative AI-supported education.

Sources were excluded from the conceptual synthesis when they lacked sufficient relevance to the research focus, were primarily concerned with technical or computational issues without a meaningful educational or learner-centred dimension, substantially replicated evidence already represented in the synthesis, or did not provide adequate conceptual or empirical relevance to the relationships under investigation. Accordingly, literature discussing AI or digital technologies exclusively from a technical perspective, without significant links to learning, pedagogy, learner experience, engagement or educational implications, was excluded from the framework synthesis.

Data Extraction and Thematic Analysis

Qualitative thematic and conceptual analysis was applied to the selected literature. Relevant information was extracted with attention to the principal concepts, theoretical perspectives, technological affordances, pedagogical implications, learner processes, engagement dimensions, and ethical or contextual issues identified across the literature. Particular attention was given to findings that explained how intelligent technologies shape learning experiences and to evidence illuminating circumstances in which personalization might facilitate or hinder learner participation and agency.

The analysis focused on identifying commonalities and relationships across the literature while examining convergence, complementarity, and conceptual tensions. Five interconnected domains emerged through an iterative process of comparison and conceptual synthesis: (1) technological intelligence; (2) learner agency and self-regulation; (3) human-centred pedagogy; (4) multidimensional student engagement; and (5) ethical and sustainable foundations. The analysis also revealed two key tensions relevant to intelligent personalization: the tension between technological adaptation and meaningful educational engagement, and the tension between automation and learner autonomy. These tensions were subsequently integrated into the conceptualization of HCIEF.



Conceptual Framework Development

The **Human-Centered Intelligent Engagement Framework (HCIEF)** was developed by conceptually integrating the themes identified in the literature. Rather than considering technology as a direct or deterministic source of student engagement, intelligent personalization is framed as a socio-technical practice in which technological intelligence interacts with learner agency and self-regulation, is informed by human-centred pedagogy, and operates through multidimensional engagement within ethical and sustainable contexts.

Within HCIEF, technological intelligence represents an enabling and augmenting layer that can analyze learner data, modify learning experiences, create or suggest resources, and provide personalized support. These technological affordances are situated in relation to learner agency and autonomy and to educator judgement. Engagement is therefore theorized as multidimensional, encompassing behavioural, cognitive, emotional, and agentic engagement, while ethical and sustainable foundations permeate the system as normative conditions. The framework is consequently understood as a conceptual integration of the reviewed literature rather than a tested causal model. Its proposed relationships constitute theoretically guided propositions that can be examined through future quantitative, qualitative, mixed-methods, longitudinal, or intervention-based research.

Methodological Rigor

Rigor was supported by conducting a **structured search** across multiple academic databases and search engines, defining the temporal scope and selection criteria, incorporating both seminal and contemporary scholarship, and organizing the selected literature through a systematic thematic structure. The use of multiple databases facilitated broader coverage of relevant literature across education, educational technology, learning sciences, and AI-related educational research.

As this study constitutes a **critical and thematic review aimed to conceptual framework development rather than a formal systematic review with quantitative synthesis**, conventional participant-based validity and reliability procedures were not applicable. Instead, methodological rigor was considered in terms of the scholarly relevance of sources, consistency of thematic interpretation, comparability across different strands of literature, and traceability between the synthesized themes and the resulting conceptual framework. The PRISMA-style flow diagram is included to further enhance transparency regarding the literature identification and selection pathway.

Analytical Orientation

The analysis was guided by a central theoretical question: **When and how can intelligent personalization in VLEs be expected to support meaningful, multidimensional student engagement while preserving learner agency, self-regulation, human-centered pedagogy, and ethical responsibility?**



Accordingly, the review considered both the opportunities and challenges associated with intelligent personalization. Particular attention was given to the potential of AI and related technologies to enhance responsiveness, customize individual support, provide feedback, and tailor learning experiences, alongside potential risks associated with over-automation, learner dependence, reduced autonomy, privacy concerns, algorithmic responsibility, digital inequality, accessibility, and changing educator roles. This analytical orientation provided the basis for integrating the identified dimensions into HCIEF.

RESULTS

The thematic synthesis identified five closely interconnected domains that characterize meaningful intelligent personalization in Virtual Learning Environments: **technological intelligence; learner agency and self-regulation; human-centered pedagogy; multidimensional student engagement; and ethical and sustainable foundations**. These domains were not treated as independent components but as mutually interacting conditions within a dynamic learning ecosystem.

The **first** finding concerns the changing nature of personalization. The literature indicates a movement from relatively predefined adaptation of content, pace, and learning pathways towards more dynamic forms of personalization supported by learning analytics, AI, conversational systems, generative AI, and adaptive technologies. Technological intelligence therefore expands the capacity of VLEs to sense learner activity, analyse patterns, adapt learning experiences, generate resources, and provide individualized support. However, technological capability emerged as an **enabling condition rather than an educational outcome in itself**.

The **second** finding concerns the centrality of **learner agency and self-regulation**. Personalization is more meaningful when learners can establish goals, make choices, monitor progress, evaluate recommendations, request alternative explanations, and influence their learning pathways. The synthesis therefore distinguishes between personalization *for* learners and personalization *with* learners. The latter provides a stronger basis for agentic engagement because learners participate in shaping the personalization process rather than simply receiving algorithmically determined adaptations.

The **third** finding concerns the continuing importance of **human-centered pedagogy**. AI can undertake functions such as pattern identification, recommendation, adaptive sequencing, content generation, and immediate feedback, but pedagogical interpretation, contextual judgement, relational support, and ethical decision-making remain important human functions. The findings consequently support a complementary human-AI relationship rather than a substitution model.

The **fourth** finding concerns the nature of **student engagement**. The synthesis supports a multidimensional conception comprising behavioral, cognitive, emotional, and agentic engagement. Conventional platform indicators primarily capture observable participation and therefore provide an incomplete representation of engagement in intelligent VLEs. Agentic engagement is particularly important because learners can increasingly question recommendations, request clarification, modify pathways, and contribute to subsequent personalization. Engagement consequently



functions not only as an outcome of personalization but also as a source of feedback within the personalization process.

The **fifth** finding concerns the **ethical and sustainable conditions** within which intelligent personalization operates. Privacy, data protection, transparency, algorithmic fairness, accessibility, digital equity, learner autonomy, digital well-being, and institutional sustainability emerged as cross-cutting requirements rather than supplementary safeguards. A technically sophisticated system cannot be considered successful if its personalization mechanisms compromise learner autonomy, reinforce inequity, or exclude particular groups.

Human-Centered Intelligent Engagement Framework

The integration of these findings resulted in the **Human-Centered Intelligent Engagement Framework (HCIEF)**. The framework conceptualizes intelligent personalization as a dynamic human-technology-pedagogy ecosystem in which technological intelligence interacts with learner agency and self-regulation and human-centered pedagogy to create conditions for multidimensional engagement. Ethical and sustainable foundations operate across the entire system. **Figure 3** presents HCIEF as a dynamic human-technology-pedagogy ecosystem rather than as a linear input-output model.

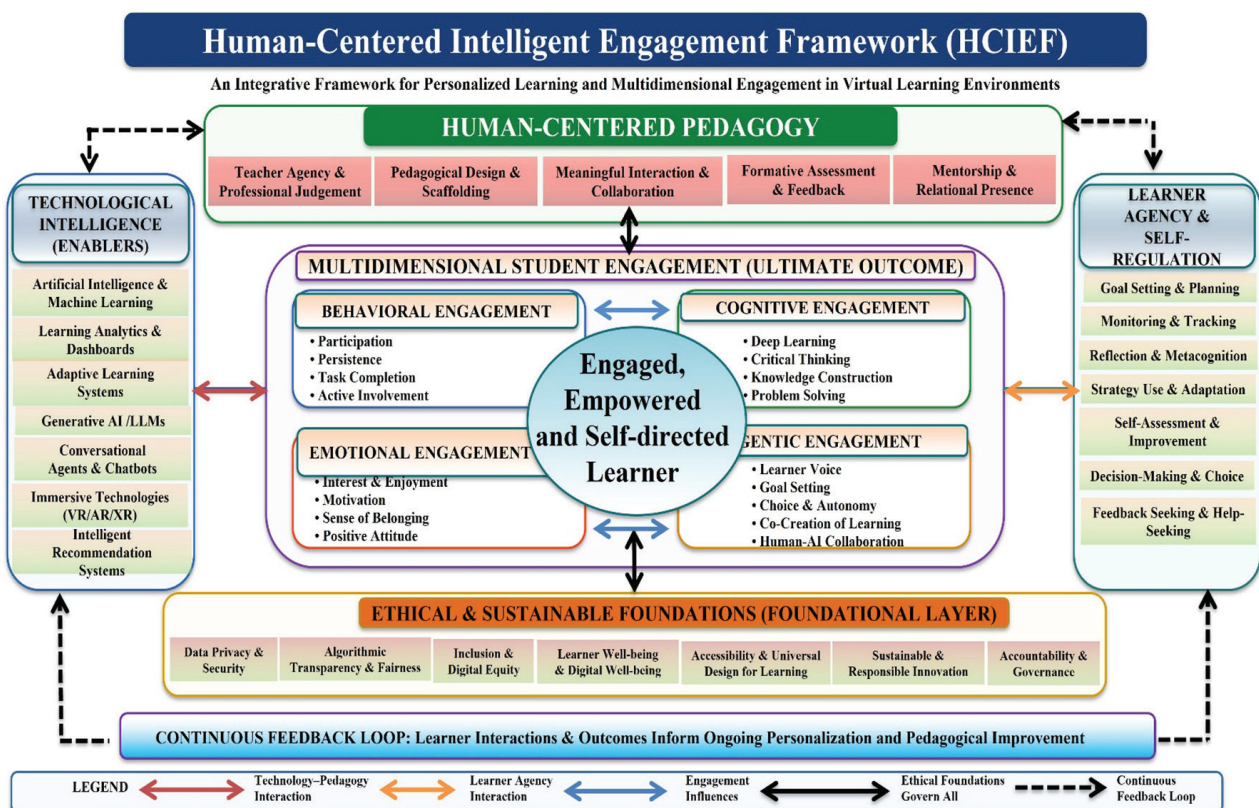


Figure 3. Human-Centered Intelligent Engagement Framework (HCIEF) for Personalized Learning and Multidimensional Student Engagement in Virtual Learning Environments



The architecture positions **technological intelligence** as an enabling mechanism that interacts with **learner agency and self-regulation** and **human-centered pedagogy**. These interacting processes create conditions for **multidimensional student engagement**, comprising behavioral, cognitive, emotional, and agentic engagement. **Ethical and sustainable foundations** operate across the entire system as a normative and contextual condition rather than as a separate stage of implementation.

The framework is therefore **reciprocal rather than deterministic**. Intelligent technologies provide information, adaptation, feedback, recommendations, and support; learners interpret, accept, question, modify, or reject these affordances; educators provide pedagogical direction and contextual judgement; and learner engagement generates further information that can inform subsequent personalization. Ethical principles govern these interactions throughout the cycle. The five interconnected domains of HCIEF, their core functions, and their respective relationships with student engagement are summarized in **Table 1**.

Table 1. Domains, Core Functions, and Engagement Relationships of the Human-Centered Intelligent Engagement Framework (HCIEF)

HCIEF Domain	Core Function	Relationship with Engagement
Technological Intelligence	Sensing, analysing, adapting, generating and supporting	Enables responsive personalization
Learner Agency & Self-Regulation	Goal setting, choice, monitoring, reflection and decision-making	Gives personalization learner direction
Human-centered Pedagogy	Design, scaffolding, feedback, interaction and judgement	Gives personalization pedagogical purpose
Multidimensional Engagement	Behavioral, cognitive, emotional and agentic participation	Represents educational consequences and generates feedback
Ethical & Sustainable Foundations	Privacy, fairness, accessibility, equity, autonomy and well-being	Establishes conditions and boundaries for responsible personalization

The distinctive architecture of HCIEF can therefore be represented as:

Technological Intelligence + Learner Agency + Human-centered Pedagogy → Multidimensional Engagement → Learner Feedback and Interaction → Further Personalization

with **ethical and sustainable foundations operating throughout the cycle**.

The central conceptual proposition emerging from the synthesis is:

Intelligent technologies are most likely to enhance student engagement in personalized VLEs when technological adaptation is integrated with learner agency and self-regulation, human-centered pedagogy, and multidimensional engagement within ethical and sustainable conditions.

This proposition is explicitly conditional rather than deterministic. Greater technological sophistication does not necessarily produce greater engagement; its educational value depends on



the alignment of technological affordances with learner needs, pedagogical purposes, opportunities for agency, and ethical requirements.

DISCUSSION

The findings indicate that personalized learning in VLEs is undergoing both a technological and conceptual transformation. Earlier approaches primarily emphasized adaptation of content, pace, and learning pathways, whereas contemporary environments increasingly incorporate learning analytics, AI, adaptive systems, conversational agents, and generative AI. Although these developments substantially expand the possibilities for individualized learning, the synthesis does not support the assumption that technological sophistication automatically produces meaningful personalization or stronger engagement.

From Adaptive Personalization to Human-centered Intelligent Personalization

The findings extend the conventional understanding of personalization by distinguishing between technological adaptation and educational personalization. Contemporary AI systems can generate individualized explanations, recommendations, feedback, and resources, but an individualized technological response does not necessarily constitute personalized learning. Personalization becomes educationally meaningful when these capabilities are connected to learning goals, cognitive engagement, self-regulation, learner agency, and pedagogical interaction. This distinction is particularly important in generative AI environments, where the apparent flexibility of interaction can create an impression of personalization even when learners remain passive recipients of AI-generated outputs.

Personalized, timely feedback is one of the key mechanisms through which AI-based personalization can affect learning outcomes. AI-enabled systems can evaluate learner responses, identify the areas in which they are facing difficulty, offer targeted explanations to those areas, and finally, produce feedback that is personalized to the performance of each learner. Recent meta-analytic evidence supports this possibility. A systematic review with meta-analysis of 40 peer-reviewed papers that included 5,849 participants revealed a small to medium positive within-group effect of AI-based personalized feedback on learning outcomes and a large positive within-group effect on learning motivation, though effect sizes were shown to vary based on learner levels, intervention durations and types of feedback (Wang et al., 2026). Additionally, a meta-analysis of 36 experimental and quasi-experimental research examining the impact of generative AI feedback on academic performance indicated a small to moderate positive effect, albeit with considerable heterogeneity and significant moderation by teaching approach (Huang et al., 2026). These results imply that the educational effectiveness of AI-produced feedback may not only depend on its immediacy or level of personalization, but also the manner in which feedback is applied in the learning environment.

There is also evidence that cautions us not to consider an AI feedback as better than a human feedback. A meta-analysis of 41 studies including 4,813 students reported an opposite effect



where no statistically significant differences were found between students receiving AI-generated feedback and students receiving human-delivered feedback on learning performance, which implied that feedback from AI might be as good as that from human in certain conditions rather than being inherently better (Kaliisa et al., 2026). In line with this, a systematic review of 129 peer-reviewed papers concluded that AI-supported feedback can facilitate task, process, self-regulation, and self-focused feedback while highlighting the significance of pedagogical integration and learner-centric design (Ba et al., 2025). Therefore, in HCIEF, AI-enabled feedback is not considered to replace educator feedback, but to be an open-ended and responsive pedagogical tool that has the potential to enhance access to feedback, reflection, revision and self-regulated learning. The success of feedback for learning is dependent on the quality of the feedback, the learning task, the learner engaging with the feedback and the ongoing engagement of the educator in offering contextual and pedagogical judgement.

Reframing Engagement in Intelligent VLEs

The findings also support a broader conceptualization of student engagement. Behavioral indicators remain useful but are insufficient for understanding engagement in intelligent environments because digital activity cannot fully capture cognitive investment, emotional experience, or learners' influence over the learning process. The inclusion of agentic engagement is therefore particularly consequential. It recognizes learners not simply as recipients of adaptive instruction but as participants who can negotiate goals, question recommendations, request alternatives, and shape subsequent interactions. This position is consistent with the multidimensional conception established by Fredricks et al. (2004) and extended through agentic engagement by Reeve and Tseng (2011). It also reinforces the argument that the effectiveness of intelligent personalization should be evaluated not merely by the accuracy of adaptation but by the extent to which adaptation supports meaningful learner participation.

The Continuing Role of the Educator

The results do not support a technology-substitution theory of AI in personalized learning. Instead, they suggest a redefinition of the role of the educator. AI can perform the computation of processing learner data, suggesting resources, customizing learning paths, creating content, and providing instant feedback, but educators are still essential for contextual understanding, pedagogical choices, learner support, and ethical considerations. Evidence from GenAI-supported learning also suggests that teacher presence can influence how students interact with AI-augmented learning. Li et al. (2026), in a mixed-methods study of students learning with a generative AI chatbot, found that students who perceived teacher presence reported significantly higher emotional and agentic engagement than students who did not perceive teacher presence, although there were no significant differences in behavioral and cognitive engagement between the two groups. These results indicate that the role of educators in AI-augmented environments may be especially crucial for maintaining the relational and agentic aspects of engagement, rather than just enhancing



surface-level participation. Thus, teacher presence serves as a human mediating layer through which learners make sense of AI-generated information, are guided pedagogically, and remain engaged in learning. Hence, intelligent personalization does not do away with the educator but rather changes the educator's role to one of shaping learning experiences, making sense of learner information, facilitating engagement, helping learners make choices, and making pedagogical and ethical judgements. This means that effective implementation of intelligent personalization requires not only technological proficiency but also educator AI literacy, pedagogical capacity, and professional judgement.

HCIEF as an Integrative Conceptual Contribution

The principal theoretical contribution of the study is HCIEF. Its significance lies less in proposing another technological model and more in integrating domains that are frequently examined separately: technological intelligence, learner agency and self-regulation, human-centered pedagogy, multidimensional engagement, and ethical and sustainable foundations. The framework shifts the analytical focus from "what intelligent systems can do" to "how intelligent capabilities should be organized around human learning." This distinction gives the framework explanatory value beyond a technology-centered account of personalization. It also provides a conceptual basis for examining why technically sophisticated systems may produce different educational outcomes across contexts. Therefore, learning outcomes within HCIEF are best conceptualized as downstream educational consequences that arise from the interplay between technological affordances, learner engagement, pedagogical mediation, and contextual factors.

The Technology-Agency Tension

A central finding is the tension between automation and learner agency. Automation can reduce the cognitive and logistical burden of navigating complex learning environments by recommending resources, identifying difficulties, and providing immediate support. Yet the same automation can reduce opportunities for learners to make decisions, experience productive difficulty, and regulate their own learning. Accordingly, the success of intelligent personalization should not be judged by the extent to which educational decisions are automated. In some circumstances, retaining learner choice, requiring reflection, and allowing learners to question or override recommendations may be pedagogically preferable to complete automation. This represents an important theoretical implication of HCIEF: responsiveness and autonomy should be balanced rather than treated as competing objectives.

Ethical and Sustainable Foundations

The results also suggest ethics should be considered a structural condition of intelligent personalization, not an afterthought added after technology has been implemented. Transparency is especially relevant here, as learners and educators may otherwise have limited means to



understand how learner data are being interpreted, how recommendations are being generated, or why specific learning pathways are being recommended. The literature on human-centred learning analytics and AI in education highlights transparency, human control, trustworthiness, and the involvement of stakeholders as key elements for the responsible design and implementation of these systems (Alfredo et al., 2024). Similarly, studies on explainable AI in education show that explainability can enhance the interpretability of decisions made by AI systems in education and help build trust and appropriate usage (Türkmen, 2025).

These are of practical use to institutions and VLE developers. Learning environments for the Personalized Learning paradigm would need to include transparency, explainability, data protection, accessibility, learner autonomy and digital well-being as design principles in the design of the environments. Digital well-being is important, as intelligent personalization may amplify the depth and continuity of technology-based learning via persistent suggestions, feedback, monitoring, and conversational support. Recent systematic review-based evidence demonstrates that AI-enabled personalized learning has the potential to improve adaptivity in learning, promote higher student engagement, and facilitate content and feedback personalization based on individual learner needs while also raising ethical, privacy, and implementation concerns (Merino-Campos, 2025). In the same way, a systematic review on ChatGPT (software) in higher education observed that generative AI can offer cognitive and emotional assistance that can support teaching and learning processes and positively impact learning and engagement; conversely, its abuse could undermine autonomy learning by fostering a dependency on AI-produced materials while contributing to technostress (Abdallah et al., 2025). The results imply that the educational worthiness of intelligent personalization is not determined solely by the existence or shrewdness of AI-based assistance, but rather by how these tools are weaved into the wider fabric of study and interaction for learners. Thus a human-centered approach needs to consider not only whether AI systems enhance engagement and customize learning, but also whether they enable sustainable forms of participation without fostering over-reliance on technology or discouraging independent learning. Intelligent personalization, therefore, should be built in a way that adds to, rather than detracts from, a learner's technological load, while still leaving room for independent thought, human interaction, reflection, and learner choice.

Theoretical and Practical Implications

Theoretically, HCIEF contributes a relational and human-centered account of intelligent personalization. It rejects a simple technology → personalization → engagement sequence and instead conceptualizes intelligent personalization as an iterative system in which technological capability, learner agency, pedagogy, engagement, and ethical responsibility interact. Practically, the framework suggests five principles for the design and implementation of intelligent VLEs: adaptive responsiveness, meaningful learner agency, human pedagogical oversight, multidimensional engagement, and ethical sustainability. Personalized VLEs should allow learners to exercise appropriate control over goals, pathways, resources, pacing, and support; educators should retain responsibility for pedagogical and ethical judgement; and evaluation should extend



beyond platform activity to include cognitive, emotional, and agentic engagement. The framework also implies that institutional implementation requires more than the installation of AI-enabled technologies. Infrastructure, educator professional development, data-governance policies, accessibility provisions, technical support, and mechanisms for monitoring educational and ethical consequences are necessary for sustainable implementation.

Finally, because HCIEF is derived through conceptual synthesis rather than empirical testing, its proposed relationships should be regarded as theoretically informed propositions requiring empirical examination. Future research can test the framework across educational levels, disciplines, learner populations, institutional contexts, and technological environments and examine whether the proposed relationships among technological intelligence, learner agency, human-centered pedagogy, multidimensional engagement, and ethical conditions are supported empirically.

CONCLUSION

This review and conceptual framework study examined the evolving relationship between personalized learning, Virtual Learning Environments, artificial intelligence, and student engagement, with particular attention to the conditions under which intelligent personalization can remain learner-centered. The synthesis indicates that the increasing technological capacity of VLEs has expanded personalization from relatively predefined adaptation of content, pace, and learning pathways towards more dynamic forms of intelligent adaptation supported by learning analytics, adaptive technologies, conversational systems, and generative AI. However, technological sophistication alone does not constitute meaningful personalization or guarantee improved student engagement.

The findings support a multidimensional understanding of engagement encompassing behavioral, cognitive, emotional, and agentic dimensions. While intelligent systems can facilitate participation, provide cognitive scaffolding, increase responsiveness, and support individualized learning experiences, their educational value depends on whether learners remain active participants in the learning process. In particular, the synthesis highlights the importance of learner agency and self-regulation in preventing personalization from becoming excessive technological automation. Personalization is most meaningful when learners can set goals, make choices, monitor their learning, respond to feedback, and influence the pathways through which learning is adapted.

The principal conceptual contribution of the study is the **Human-Centered Intelligent Engagement Framework (HCIEF)**. The framework integrates five interrelated domains, technological intelligence, learner agency and self-regulation, human-centered pedagogy, multidimensional student engagement, and ethical and sustainable foundations, within a dynamic human-technology-pedagogy ecosystem. Rather than proposing a linear relationship between technology and engagement, HCIEF conceptualizes personalization as a reciprocal process in which technological adaptation, learner participation, pedagogical judgement, and engagement continuously inform one another. This provides a human-centered perspective for understanding intelligent personalization beyond technological functionality.



The framework has implications for both theory and practice. Theoretically, it contributes to the emerging literature by bringing technological intelligence, learner agency, pedagogy, and engagement into an integrated conceptual structure. Practically, it suggests that institutions and VLE designers should evaluate intelligent personalization not only in terms of adaptive accuracy or platform activity but also in terms of cognitive investment, emotional experience, learner agency, educator involvement, accessibility, privacy, equity, and digital well-being. AI should therefore be positioned as an augmentation of pedagogical capacity rather than a replacement for learner decision-making or educator judgement.

The future of personalized learning in virtual learning environments will not be determined simply by how intelligent educational technologies become, but by what we choose to do with that intelligence. Artificial intelligence can increasingly recognize patterns, generate explanations, recommend resources, adapt learning pathways, and respond to individual learners in ways that were difficult to imagine in earlier generations of digital learning. Yet the ability to personalize a learning experience technologically does not necessarily mean that the experience has become more meaningful, humane, or educationally valuable.

The more important question, therefore, is not whether learning environments can become increasingly intelligent, but whether they can become increasingly responsive without becoming increasingly controlling. A genuinely personalized environment should not merely know more about learners; it should enable learners to know more about themselves, make informed choices, question recommendations, regulate their learning, and participate in shaping the experiences through which they learn. In this sense, the future of personalization may depend as much on preserving learner agency as on advancing algorithmic capability.

LIMITATIONS

This study has multiple limitations. First, the Human-Centered Intelligent Engagement Framework (HCIEF) is the result of an interpretative synthesis of existing literature and is an unprecedented model in this area of research. Hence the proposed associations between its domains should be seen as theoretically informed hypotheses rather than confirmed causal links. Second, the literature deals with whole a new set of emerging technologies (e.g., generative AI), technological evolution may be so fast that some of the evidence considered in this review could become outdated. Third, variations in educational settings, institutional resources, learner demographics, and AI types might also affect how personalization and engagement are manifested and thus how well the framework can be applied consistently across settings. Fourth, the evidence base may be subject to publication bias, given the acceleration in research reporting positive or promising uses of AI in education, and the predominantly English-language literature may limit the inclusion of evidence from non-English-speaking educational systems. Finally, as the study is conceptual and literature-based, it does not provide direct evidence of the processes through which learners and educators personalize intelligent personalization in particular teaching and learning contexts.



FUTURE RESEARCH

Future studies should take an empirical focus on HCIEF at varying educational levels, within different disciplinary fields, across diverse learner populations and types of institutional environments, and among various VLE platforms. Quantitative analyses could operationalize the domains of the framework and examine the hypothesized structural associations among technological intelligence, learner agency and self-regulation, human-centered pedagogy, and the behavioral, cognitive, emotional, and agentic aspects of involvement. Psychometric research may also build upon and further validate the measures developed for the major HCIEF constructs. Qualitative and mixed methods research could explore how students and instructors engage with, make sense of, negotiate and react to AI-mediated personalization in real-world learning environments. There is especially a need for longitudinal research to assess if AI-enhanced personalization leads to lasting gains in engagement and self-regulation rather than temporary increases in platform activity that are easily observable. A related line of comparative and experimental inquiry might also address whether and how varying degrees of automation support or undermine learner agency and decision-making. The impact of teachers' AI literacy, pedagogical skills, privacy concerns, algorithmic fairness, accessibility, digital equity, transparency and digital well-being on the effective delivery of human-centred intelligent personalization should be the focus of subsequent studies.

ARTIFICIAL INTELLIGENCE (AI) DISCLOSURE

The use of AI tools was limited and served only a supportive role in the writing and editing of this manuscript. The manuscript text was edited with OpenAI's ChatGPT (GPT-5.6 Luna) for assistance in language refinement, rewording, and editorial enhancement, for clarification and organization of academic arguments, as well as for the composition of paragraphs during revisions. In addition, AI assistance was employed in the literature-searching process for planning and identifying potential relevant academic documents; all referenced documents were additionally assessed and confirmed by the authors prior to inclusion. ChatGPT was further involved in conceptual figure development and refinement (Figs. 1 and 2); the figures were subjected to critical review, revision and finalization by the authors in order to ascertain congruency with the proposed Human-Centered Intelligent Engagement Framework (HCIEF). The modeled research, critical review and analysis of the literature, design and development of HCIEF, scholarly obligations, source verifications, and conclusive decisions related to the paper are the authors' own. Every AI-generated content, output or result must be critically analyzed, checked for facts, edited and verified by the authors. The authors declare that they have full responsibility for the content of this manuscript in terms of accuracy, originality, academic integrity, ethics, and final completeness.

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