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Integrating AI into educational game design: an AI-enhanced MDA framework

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This study proposes an artificial intelligence (AI)-enhanced framework that integrates AI with the Mechanics, Dynamics, and Aesthetics framework through theory synthesis and framework development. It explores how generative AI, adaptive learning algorithms, and procedural content generation enhance gameplay to advance educational game design. The framework aligns AI capabilities with constructivist learning principles, supporting personalized, engaging, and scalable game-based learning. While the framework offers theoretical and practical guidance for AI-integrated educational games, further research is needed to assess its empirical effectiveness across diverse learning settings.

Keywords: AI-enhanced framework; MDA framework; educational game design; game-based learning; constructivist learning

Introduction

The integration of artificial intelligence (AI) into education and game-based learning offers new opportunities for designing adaptive and engaging learning environments. However, existing theoretical frameworks often fail to capture the transformative potential of AI within these domains. Several established game-design and learning frameworks clarify features of engagement and learning (Koster, 2013; Schell, 2008; Sweetser & Wyeth, 2005), but they do not provide a clear analytical mapping that locates AI functions within game rules, runtime behaviours, and player experience in a way that is actionable for educational designers. This study addresses this gap by extending the well-developed Mechanics, Dynamics, and Aesthetics (MDA) framework (Hunicke et al., 2004) to incorporate AI-enhanced capabilities. We argue that AI should be treated as a cross-cutting, constitutive design axis because modern AI techniques (e.g. generative models, reinforcement/adaptive systems, PCG) simultaneously alter mechanics (rule definitions), dynamics (emergent play and interaction patterns), and aesthetics (player experience and affect). The proposed framework systematically explains how AI technologies, such as generative AI, adaptive learning algorithms, and procedural content generation (PCG) support and enhance core game design principles. It provides

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a comprehensive structure for understanding the evolving role of AI in educational game design and its impacts on game-based and constructivist learning.

Literature review

AI in game-based learning

AI-driven educational games are increasingly used to support adaptive instruction, personalized feedback, and dynamic learning experiences. The intelligent tutoring systems (ITS) literature shows that embedded AI can improve learning outcomes by delivering individualized feedback and scaffolding (Anderson et al., 1995; VanLehn, 2011). Work on adaptive hypermedia and personalization demonstrates how systems that model learners can tailor content sequencing and difficulty (Brusilovsky, 2001). Recent overviews of AI in games document how AI methods from player modelling to PCG change the possibilities for design and evaluation of game experiences (Shaker et al., 2016; Yannakakis & Togelius, 2018). These literatures provide the empirical and conceptual basis for incorporating AI into game design frameworks intended for learning contexts.

MDA framework and why it was selected

MDA (Hunicke et al., 2004) is a formalized lens that distinguishes between mechanics (rules and systems specified by designers), dynamics (runtime behaviours emerging from mechanics and player interaction), and aesthetics (the emotional responses and experiences of players) (see Figure 1).

It consists of three parts:

Mechanics: These are the basic rules and systems in a game. Mechanics define what players can do. Examples include movement, scoring systems, and resource management.

Dynamics: These describe how the mechanics interact when the game is played. It includes how the rules create different challenges or experiences.

Aesthetics: This refers to the emotional experience that players have while playing. It includes visual design, storytelling, and the feelings a game creates. For instance, a horror game uses dark environments and suspenseful music to make players feel fear.

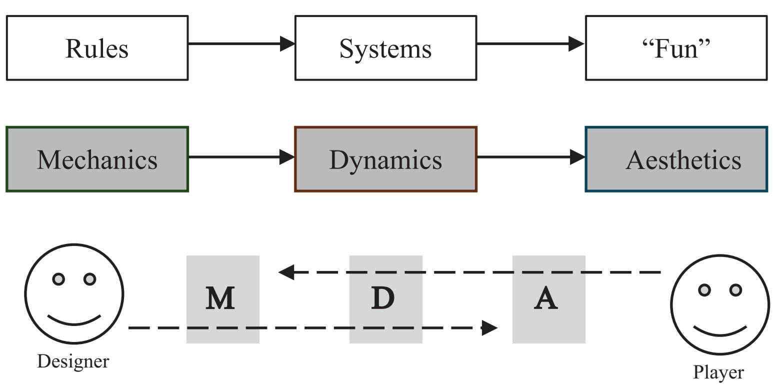

Figure 1. The MDA (mechanics, dynamics, aesthetics) framework (Hunicke et al., 2004).

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The MDA framework helps designers think about how a game's rules (Mechanics) lead to different interactions (Dynamics), which then create player experiences (Aesthetics).

MDA's explicit triadic separation makes it particularly suitable for mapping how AI interventions operate at different design granularity, such as AI can alter rule encodings (mechanics), dynamically mediate play (dynamics), and change affective outcomes (aesthetics). While descriptive frameworks such as Koster's A Theory of Fun (Koster, 2013) and Schell's The Art of Game Design (Schell, 2008) provide valuable design heuristics, they do not provide an analytical structure that clearly supports locating algorithmic design choices and tracing their downstream impacts on emergent behaviour and player experience. Likewise, experiential evaluation models like Game Flow (Sweetser & Wyeth, 2005) define important engagement criteria but lack the structural mapping needed to locate technical AI affordances within design artifacts. Therefore, MDA was selected because it offers a rigorous separation of layers that is necessary to theorize and evaluate how AI functions become embedded in game design.

Why AI is a missing-but-essential element

Originally developed before modern machine learning and widespread procedural generation, MDA implicitly assumes relatively static mechanics. Contemporary AI shifts that assumption, such as PCG creates content continuously (Shaker et al., 2016), player modelling enables individualized choices (Yannakakis & Togelius, 2018), and adaptive systems modify game rules in real time (VanLehn, 2011; Woolf, 2010). In educational contexts, the literature on ITS, personalization, and adaptive learning demonstrates that algorithmic adaptivity influences not only task difficulty but also learner motivation, cognitive load, and learning trajectories (Anderson et al., 1995; Brusilovsky, 2001). Because AI technologies operate at rule definition (mechanics), runtime adaptation (dynamics), and in shaping affect (aesthetics), they should be considered a foundational, integrated element rather than an external tool. This repositioning addresses a theoretical gap and improves our ability to prescribe design choices for learning outcomes.

Existing AI-inclusive work and the remaining gap

A growing set of studies examine AI capabilities in games, for example, player modelling and experience-driven PCG (Summerville et al., 2018; Yannakakis & Togelius, 2018) and other works focus on the educational effects of adaptive learning systems (VanLehn, 2011). However, these contributions are typically oriented either around technical algorithms or around educational evaluation. What is missing is a theory-driven synthesis that positions AI capabilities within a layered game-design model, explicates cross-layer interactions (how an AI-driven mechanic shapes dynamics and aesthetics), and links these to educational mediators and outcomes (e.g. engagement, cognitive load, learning gains). The present AI-enhanced MDA framework aims to fill that gap by synthesizing AI, game design, and learning-science literatures into a prescriptive and testable conceptual model.

The need for an AI-integrated framework

AI technologies such as deep learning, reinforcement learning, and PCG are revolutionizing digital content creation (Summerville et al., 2018). These methods enable real-time adaptation, content diversity, and player modelling that can support educational strategies such as scaffolding and adaptive practice (Woolf, 2010). Because the MDA framework predates many of these technological advances, it lacks explicit guidance for mapping AI functions into game design. Thus, a formal augmentation of MDA that embeds AI as a cross-cutting axis is necessary to guide designers who intend to meet both learning and engagement objectives.

Research aim

This study aims to develop an AI-enhanced game design framework based on the MDA framework, incorporating AI's role in enhancing game MDA by integrating AI components into that framework.

Research questions

RQ 1: How do AI capabilities map onto the mechanics layer?
RQ 2: How do AI capabilities influence dynamics?
RQ 3: How do AI capabilities alter aesthetics in educational contexts?
RQ 4: How can these mappings be integrated into a coherent AI-enhanced MDA framework that informs design and evaluation for learning outcomes?

Methodology

This study employs theory synthesis and framework development informed by design-science principles and conceptual framework-building procedures. We follow Torraco's (2005) approach to theory synthesis, Jabareen's (2009) steps for constructing conceptual frameworks, and Hevner et al.'s (2004) design-science criteria to ensure the model is both theoretically grounded and practically actionable. The process consists of three main stages: (1) selection and analysis of existing frameworks, (2) integration of AI components, and (3) development of an AI-enhanced framework.

Selection and analysis of existing frameworks

The MDA framework (Hunicke et al., 2004) was chosen due to its explicit triadic separation that supports mapping between design artifacts and player experience, its wide adoption in game design research, and its conceptual compatibility with learning-science constructs. We compared MDA to alternate frameworks (Koster, 2013; Schell, 2008) and concluded that MDA's layered clarity is most useful for locating algorithmic affordances and for articulating design prescriptions linked to educational outcomes.

Use AI as a unifying element

It involves identifying AI applications that enhance game design. The integration of these AI elements is guided by design science research principles, which emphasize

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the development of frameworks to solve real-world problems (Hevner et al., 2004). Enrolling AI into the MDA framework helps to create a more adaptive approach to game design.

Step 1: Identifying suitable AI elements. Based on an extensive literature review, we identified three primary AI families that are most relevant for educational games:

- Generative AI (content & narrative generation) which is relevant for producing varied tasks, stories, and assets (Summerville et al., 2018).
- Adaptive learning algorithms & player modelling which are relevant for sequencing, feedback, and personalization (Brusilovsky, 2001; VanLehn, 2011).
- PCG which is for level, task, and challenge generation that improves replay ability and alignment to learner needs (Shaker et al., 2016).

Each dimension was evaluated for generativity, adaptability, cognitive-load effects, and interactivity using criteria derived from the learning sciences and game research (Sweller et al., 1998).

- Generative AI:

Generative AI refers to algorithms that can produce new content or data resembling existing data, playing a pivotal role in game design by creating dynamic and personalized content (Bond et al., 2024; Chamola et al., 2024). Research indicates that Generative AI facilitates the creation of interactive game systems that adapt in real-time to player interactions, thereby supporting personalized learning (Bae et al., 2024).

- Adaptive learning algorithms:

Adaptive learning algorithms adjust game dynamics to match the player's skill level and learning pace, enhancing engagement and learning outcomes (Romero-Mendez, 2023). The integration of adaptive learning algorithms in educational game design has been shown to support real-time student interactions and personalized learning experiences (Tang et al., 2020), for example, AI-driven adaptive systems personalize game experiences by dynamically adjusting mechanics and dynamics based on player behaviour, fostering engagement (Chen, 2024).

- PCG:

PCG involves the algorithmic creation of game content with limited or indirect human input, enabling the generation of vast and diverse game environments, levels, or scenarios (Dahrén, 2021). This technique enhances professional creativity by allowing designers to focus on higher-level creative tasks while algorithms handle content generation (Kruse, 2019). AI techniques like PCG automate the creation of game content, allowing for endless variations and reducing the cognitive limitations on designers (Yannakakis & Togelius, 2018).

Step 2: Evaluating AI Contributions to Game Design. The selection of following aspects as the evaluation criteria for AI's contribution to game design is based on existing research that highlights their critical role in enhancing play experiences. All of these aspects have been extensively studied in the AI-driven game design literature which proves their direct impact on player engagement.

- Generativity:

This refers to the AI's ability to produce new and meaningful content, such as narratives, visuals, or game levels. Evaluating an AI tool's generative capabilities involves assessing the quality, diversity, and relevance of the content it creates (Summerville et al., 2018).

- Adaptability:

An AI's ability to dynamically respond to user input and adjust experiences accordingly is critical for maintaining player engagement. Evaluating adaptability involves examining how well the AI adjusts game mechanics, difficulty levels, or narratives based on player behaviour (Yannakakis & Togelius, 2018). Research highlights the fact that adaptive AI improves player engagement by modifying game mechanics, narratives, or difficulty levels in response to real-time player behaviour (Westera et al., 2020).

- Cognitive load reduction:

AI tools that automate repetitive tasks can ease the cognitive burden on designers, allowing them to focus on higher-order creative decisions. Assessing this aspect involves determining how effectively the AI streamlines workflows and enhances productivity (Niederman, 2021). This aspect directly impacts the efficiency of the design process, making it a necessary consideration in evaluating AI tools (Gkintoni et al., 2025).

- Interactivity:

Interactivity is a fundamental component of AI-driven game design, ensuring that AI fosters meaningful interactions between players and the game world (Alam & Mohanty, 2023). Research confirms that AI-enhanced interactivity leads to higher engagement, deeper decision-making, and more immersive gameplay experiences (Esiri, 2022).

Development of an AI-enhanced framework

This process is guided by framework development methodologies (Jabareen, 2009), ensuring that the proposed framework integrates AI and game design insights into a structured model. This model merges AI-driven features, such as generative AI, adaptive learning, and PCG with the combined framework derived from the MDA framework.

Findings

The following represents the conceptual mappings derived from the literature. Each mapping is grounded in cited work that demonstrates the mechanism and its implications for learning.

Generative AI

Mechanics. Generative AI enables dynamically defined rules and content templates rather than static, hand-authored artifacts (Shaker et al., 2016; Summerville et al., 2018). This reduces dependencies on fixed content and allows rules to be parameterised by learner models.

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Additionally, generative AI facilitates the automatic creation of game elements, such as rules, quests, and levels, enabling personalized gameplay experiences (Rantanen, 2023). This technology allows for the development of dynamic content that adapts to individual player preferences, enhancing engagement (Hall, 2024).

Dynamics. Generative AI supports adaptive pacing and emergent content interactions which enhances player interaction and engagement (Oliveira & Rito, 2024; Swacha & Gracel, 2025). For example, it adjusts difficulty levels and content progression based on player behaviour to encourage players to adapt to new challenges dynamically (Ratican & Hutson, 2024b), which change how learners explore problem spaces (Summerville et al., 2018; Yannakakis & Togelius, 2018) and helps in fostering a more responsive gaming experience (Ratican & Hutson, 2024a) and also enhancing the overall gaming experience (Kas Elias & Salaimeh, 2024).

Aesthetics. Generative AI increases novelty, presence, and immersion, features associated with deeper engagement and intrinsic motivation in learning settings (Ryan et al., 2006; Yannakakis & Togelius, 2018). It contributes to aesthetic elements by creating stories that can resonate emotionally with players (Antony & Huang, 2025; Song et al., 2024).

By leveraging AI-driven content generation, games can offer unique visual and auditory experiences (Samson, 2024), thereby enhancing player engagement and satisfaction (Ratican& Hutson, 2024b).

Adaptive learning algorithms

Mechanics. Adaptive algorithms operationalise rules that change in response to learner state (Woolf, 2010) which is tailoring game mechanics to individual player needs by analysing performance data and adjusting challenges accordingly (Hossan et al., 2024; Paraschos & Koulouriotis, 2023). These mechanics explicitly encode educational policies and ensure that game mechanics remain engaging and appropriately challenging, fostering a more effective learning environment (Chiotaki et al., 2023; Ng et al., 2024).

Dynamics. These algorithms influence game dynamics by modifying the game's response to player actions in real-time (Mehta, 2025; Sayed et al., 2023), for instance, if a player struggles with a particular task, the game can adapt by providing additional support or altering the difficulty level, thereby maintaining a balanced and motivating gameplay experience (Mehta, 2025). It means that player modelling alters the tempo and sequence of learning interactions, providing scaffolding or challenges when appropriate, mechanisms known to improve retention and transfer when well-designed (Anderson et al., 1995).

Aesthetics. Adaptive systems can reduce frustration and cognitive overload by matching challenge to skill (flow), thereby improving learner confidence and engagement (Csikszentmihalyi & Csikzentmihaly, 1990), while generative AI elevates the aesthetic experience by creating immersive narratives and visually appealing assets (Guo et al., 2023; Holmes et al., 2019). The ability to generate complex game environments and characters contributes to a deeper sense of immersion and enjoyment for players (Alexiou & Schippers, 2018), which can inspire creativity and enhance the overall gaming experience (Tanskanen, 2018).

Procedural content generation

Mechanics. PCG algorithms create levels, problems, or practice items governed by parametric rules which enables large-scale content variation and targeting of specific learning objectives (Summerville et al., 2018), thereby driving the creation of game content through algorithms, such as generating levels, maps, or quests (Saffari et al., 2024). This algorithmic approach ensures a continuous supply of fresh content, keeping players engaged over extended periods (Smith, 2014).

Dynamics. PCG introduces controlled variability and unpredictability thereby fostering problem-solving flexibility, replay ability, and support for distributed practice and exposure to broader problem instances (Shaker et al., 2016). It influences game dynamics by introducing variability and unpredictability into gameplay (Sel, 2025). This variability requires players to adapt their strategies, which enhances replay ability and maintains player interest over time (DaCosta, 2025).

Aesthetics. PCG supports emergent aesthetics by fostering surprise and novelty across sessions, which can sustain motivation over longer learning trajectories (Yannakakis & Togelius, 2018). By creating emergent design patterns, PCG ensures that each playthrough feels fresh and unique (Herrera & Vargas, 2025), and the variability introduced by PCG further contributes to a dynamic and immersive player experience (Lazaridis & Fragulis, 2024).

AI-enhanced game design framework

Figure 2 illustrates the proposed AI-enhanced MDA framework by mapping how different branches of AI which are Generative AI, Adaptive Learning Algorithms,

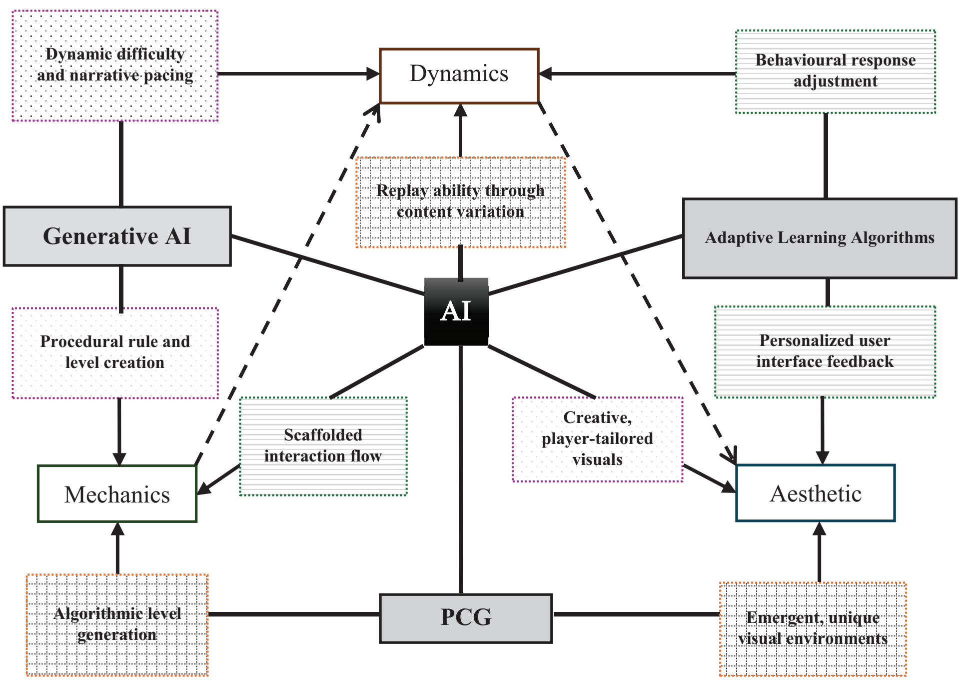

Figure 2. The AI-enhanced game design framework.

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and PCG interact with and strengthen the original MDA model. At the centre of the framework, AI functions as the integrative core that links data-driven processes to player experience design.

First, AI supports mechanics through several mechanisms. Generative AI contributes directly by enabling ‘procedural rule and level creation’, allowing game systems to evolve through algorithmic adjustments rather than static design. PCG further strengthens mechanics by providing ‘algorithm-based content generation’, which ensures continuous variability across tasks, levels, or learning challenges. These AI-supported mechanics enable more flexible and personalised structures for educational gameplay.

Second, AI influences dynamics, the real-time behaviour and progression of gameplay through adaptive processes. The diagram shows that dynamics is shaped by features such as ‘dynamic difficulty and narrative pacing’, ‘behavioural response adjustment’, and ‘replay ability through content variation’. These components demonstrate how AI monitors learner behaviour and modifies task difficulty, pacing, or scenario content to maintain meaningful engagement and sustained cognitive challenge.

Third, AI enhances aesthetics by supporting the creation of ‘creative, player-tailored visuals’, improving ‘personalised user interface feedback’, and generating ‘emergent, unique visual environments’. These elements emphasise how AI systems introduce aesthetic diversity and personalised sensory cues that align with individual learners’ preferences, accessibility needs, or motivational profiles.

The diagram also highlights cross-layer interactions. For example, ‘scaffolded interaction flow’ emerges from the collaboration between generative AI and game dynamics, while adaptive learning algorithms contribute simultaneously to dynamics and aesthetics through behaviour-responsive visual and interface adaptation. PCG feeds into both mechanics and aesthetics by producing underlying structural variability and surface-level visual differentiation.

Overall, Figure 2 demonstrates that the integration of AI into the MDA framework is not linear but multidirectional: each AI subsystem dynamically contributes to multiple components of player experience design. This expanded architecture clarifies how AI can systematically enhance mechanics-level variability, dynamics-level responsiveness, and aesthetic-level personalisation, thereby offering a more holistic model for the design of AI-supported educational games.

Discussion

The framework shows how generative AI, adaptive algorithms, and PCG connect to the MDA elements. Unlike the traditional linear mapping, the model shows multi-directional, overlapping relationships, where each AI function contributes to multiple MDA layers. This updated conceptualisation aligns with recent criticisms that the original MDA framework lacks mechanisms for representing adaptive, data-driven, and personalised gameplay processes (Ninaus & Nebel, 2021).

Compared with existing extensions of MDA or the player-centred MDA, the proposed AI-enhanced MDA offers a clearer articulation of how AI directly shapes the structural, behavioural, and experiential layers of gameplay (Sicart, 2008). Unlike previous frameworks that embed AI only as part of mechanics or data analytics, the present model positions AI as a central integrative engine that continuously mediates interactions across MDA, providing learners with personalized, adaptive experiences.

This theoretical positioning clarifies not only why AI must be considered a missing element in existing models, but also how this integrated approach improves upon existing AI-inclusive frameworks, such as ITS or dynamic difficulty adjustment models (Ninaus & Nebel, 2021).

The framework avoids assigning AI to a single layer and instead shows multi-layer interactions found in recent studies.

Generative AI contributes not only to the mechanical elements but also to dynamic narrative pacing, automated scenario branching, and creative aesthetic variability (Hall, 2024).

Adaptive algorithms personalise gameplay and shape aesthetic experiences (Chiotaki et al., 2023).

PCG supports scalable content, emergent play, and aesthetic freshness.

By integrating these functions, the framework addresses RQ1 to RQ3 by demonstrating how AI modifies the internal structures of educational games, how adaptive decision-making enhances moment to moment gameplay dynamics, and how personalised aesthetic experiences support learner engagement, curiosity, and flow. Furthermore, the framework responds to RQ4 by illustrating how AI collectively contributes to improved educational alignment, scaffolding, and learner-centred interaction design.

Overall, the model provides a new lens for understanding AI as an integrated system rather than a set of isolated tools, jointly shaping game mechanics, interaction processes, and learner experiences. This aligns with contemporary educational technology literature emphasising personalised learning ecosystems, multimodal engagement, and the integration of learner analytics into design (Holmes et al., 2019). Mapping these interconnections enables a systematic and flexible way to embed AI into MDA.

Contributions of the AI-enhanced framework

The proposed AI-enhanced framework contributes to educational game research in several ways:

First, it enhances game-based learning through dynamic, personalised content generation. By incorporating generative AI and PCG, the framework enables adaptive task variation that matches learners' evolving skills, supporting differentiated instruction and sustained challenge (Hind & Harvey, 2024).

Second, the framework contributes to teaching effectiveness by integrating adaptive learning algorithms capable of fine-tuning difficulty in real time. This supports optimal cognitive load, increases learner persistence, and aligns gameplay with instructional objectives which is an effect well-documented in adaptive learning research (Webb & Chang, 2015).

Third, the framework provides a theoretically grounded structure to guide future AI-based educational game design, addressing gaps in existing models that do not adequately represent AI-mediated adaptivity or personalisation.

Theoretical and practical implications

This study extends constructivist and sociocultural theories by demonstrating how AI-enhanced game design can support active meaning-making, personalised scaffolding, and situated problem solving core principles in learning sciences (Quintana

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et al., 2018). By embedding generative AI, adaptive learning, and PCG into the MDA model, the framework offers specific guidelines for aligning game elements with curriculum standards, learner needs, and educational intentions.

Practically, the framework can support:

- Curriculum-aligned game design that reinforces targeted competencies.
- Adaptive scaffolding that adjusts hints, pacing, and narrative clarity based on learner behaviour.
- Innovative tools, such as AI-generated dialogues, dynamic assessment, and personalized visual environments.

Limitations and future research

Despite its contributions, this study has several limitations.

First, the framework remains conceptual, and its effectiveness has not yet been validated. Further studies should include pilot tests to evaluate engagement, learning outcomes, and learner behaviours in AI-enhanced games.

Second, the model has not been examined in long-term classroom contexts. Longitudinal research is needed to examine whether AI-mediated adaptivity benefits learners over time and across different settings.

Third, further research should examine how teachers and learners perceive transparency, fairness, and ethical issues in AI-driven game environments.

Future work should therefore combine user studies, classroom trials, and design-based research to continue refining the model and validating its practical relevance.

Conclusion

This study proposed an AI-enhanced extension of the MDA framework, positioning AI as a central element shaping MDA. Future work should validate the framework through pilot studies and classroom trials to assess its impact on learning and engagement.

Conflict of interests and funding

The author declares no conflict of interest. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

This study does not involve the collection or analysis of primary datasets involving participants and no additional data are available. For further inquiries or clarifications, please contact the corresponding author.

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