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Educating in an Era of Continuous Change

Designing AI-enhanced learning environments for adult learners: A design-based framework for solving complex interdisciplinary problems

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As online adult education rapidly expands, driven by technological advancements and post-pandemic demands, there is a critical need to reimagine evaluation and learning frameworks that address the limitations of traditional methods. This study proposes a novel Design-Based Research (DBR) framework to develop AI-enhanced learning environments tailored for solving complex, real-world problems. By integrating heutagogy, authentic learning, and transformative learning theory, the research aims to create a transferable model that empowers adult learners to navigate interdisciplinary challenges. Expected outcomes include a transferable design framework, ethical AI guidelines, and scalable principles for lifelong learning, addressing gaps in traditional evaluation methods while prioritizing learner-centric and context-sensitive innovation.

Keywords: Design-Based Research, heutagogy, Artificial intelligence (AI), Adult Learners

The Need for AI-Enhanced Learning Environments for Adult Complexity

The rapid advancement of Artificial Intelligence (AI) technology has reshaped many aspects of education, especially in online learning, where adaptive learning systems, automated feedback, and data-driven insights have become increasingly prevalent. Adult learners in particular, who often balance professional, familial, and educational commitments, require flexible, adaptive learning environments that cater to their diverse needs (Knowles et al., 2014). However, conventional evaluation methods—such as standardized tests and static assessments—struggle to capture the complexity of adult learners' interdisciplinary competencies, critical thinking abilities, and evolving learning trajectories (González-Calatayud et al., 2021). While artificial intelligence (AI) offers transformative potential through tools like adaptive assessments and personalized feedback, its current applications in adult education remain largely fragmented, prioritizing efficiency over pedagogical depth and fails to address systemic challenges such as learner autonomy, ethical transparency, and real-world problem-solving alignment (Jiao, 2024; Khine, 2024).

To address these limitations, this study adopts a Design-Based Research (DBR) approach to develop and iteratively refine a framework for AI-enhanced learning environments tailored to adult learners in China. Design-Based Research (DBR) is an iterative methodology that develops and refines educational innovations in authentic contexts through cycles of design, implementation, and analysis. It bridges theory and practice by co-creating solutions with stakeholders while simultaneously generating transferable design principles and theoretical insights (Anderson & Shattuck, 2012; Wang & Hannafin, 2005). Grounded in heutagogy (Hase & Kenyon, 2000), which emphasizes learner agency and self-determination, the framework integrates authentic learning principles to align AI tools with real-world interdisciplinary tasks (e.g., collaborative problem-solving, scenario-based simulations). Simultaneously, transformative learning theory (Mezirow, 2000) guides the design of AI-supported reflective practices, enabling learners to critically examine assumptions and reshape their understanding of complex issues. To analyze the systemic dynamics of these environments, activity theory (Engeström, 2001) is employed to map interactions among learners, AI tools, educators, and socio-cultural contexts, identifying contradictions and synergies that influence learning outcomes.

Phases of DBR Implementation

Phase 1: Collaborative Design

The first phase involves a series of co-design workshops where learners, educators, and AI experts collaboratively prototype AI tools aligned with heutagogical principles and authentic learning tasks. For instance, adaptive scaffolding systems will be designed to support self-directed problem-solving, while peer evaluation platforms will integrate reflective prompts to foster critical discourse. Ethical considerations, such as algorithmic transparency and data anonymization, are prioritized during prototyping to mitigate biases and ensure compliance with privacy standards (Fahmy, 2024).

Table 1
AI Tools Co-Designed for Adult Interdisciplinary Learning

Tool Name (Abbreviation)	Core Function	Technical Implementation	Theoretical Alignment	Data Input/Output
NLP Adaptive Scaffolding Engine (NASE)	Dynamically adjusts task complexity in interdisciplinary problem-solving	Fine-tuned `bert-base-chinese` model Cognitive tiering: Bloom’ s Taxonomy keyword detection	Heutagogy (Self-determined challenge selection)	Input: Reflection journals + task performance Output: Personalized case library links
Transformative Journal Analyzer (TJA)	Triggers critical reflection through automated probing	Sentiment analysis (VADER lexicon) Assumption identification (spaCy dependency parsing)	Transformative Learning (Perspective shifting)	Input: Free-text reflections Output: Counter-evidence prompts + related literature
Cross-Domain Peer-Match (CDPM)	Pairs learners from dissimilar fields for collaboration	SciBERT embeddings Cosine similarity clustering	Activity Theory (Community-object mediation)	Input: Project proposals Output: Match list + collaborative workspace
Bias-Audited Feedback Generator (BAFG)	Provides writing feedback with fairness checks	Template-based GPT-4 fine-tuning Regional term bias detection (e.g., urban/rural terminology)	Algorithmic Justice	Input: Learner essays Output: Revision suggestions + bias report
Transformative Journal Analyzer (TJA)	Triggers critical reflection through automated probing	Sentiment analysis (VADER lexicon) Assumption identification (spaCy dependency parsing)	Transformative Learning (Perspective shifting)	Input: Free-text reflections Output: Counter-evidence prompts + related literature
Cross-Domain Peer-Match (CDPM)	Pairs learners from dissimilar fields for collaboration	SciBERT embeddings Cosine similarity clustering	Activity Theory (Community-object mediation)	Input: Project proposals Output: Match list + collaborative workspace

Phase 2: Iterative Implementation

The AI tools will be piloted in three online adult education programs over six months, including vocational training and professional development courses. Quantitative data will be collected through pre- and post-tests measuring learners’ interdisciplinary problem-solving performance, alongside engagement metrics (e.g., interaction frequency, time spent on AI tools) generated by the platforms. Qualitative data will include semi-structured interviews with 30 learners, focusing on their experiences of autonomy, tool usability, and transformative learning processes. Concurrently, focus groups with educators will explore systemic challenges, such as mismatches between institutional objectives and learner-driven goals. Reflective journals maintained by participants will provide additional insights into how AI tools influence critical reflection and perspective shifts.

Phase 3: Systemic Evaluation and Refinement

Activity theory will be employed to analyze contradictions and synergies within the AI-supported learning ecosystem. Engeström's (2001) activity system model will map interactions among learners, tools, educators, and institutional norms, identifying tensions such as resistance to AI-driven autonomy or misalignments between adaptive assessments and learners' prior knowledge. Triangulation of quantitative performance trends, qualitative narratives, and activity theory mappings will ensure robust validation of findings. For example, structural equation modeling (SEM) will test hypothesized relationships between heutagogical practices (e.g., self-goal setting) and learning outcomes, while thematic analysis (NVivo) of interview transcripts will uncover emergent themes related to transformative learning. Iterative feedback loops will guide the refinement of AI tools, with revised prototypes tested in subsequent implementation cycles.

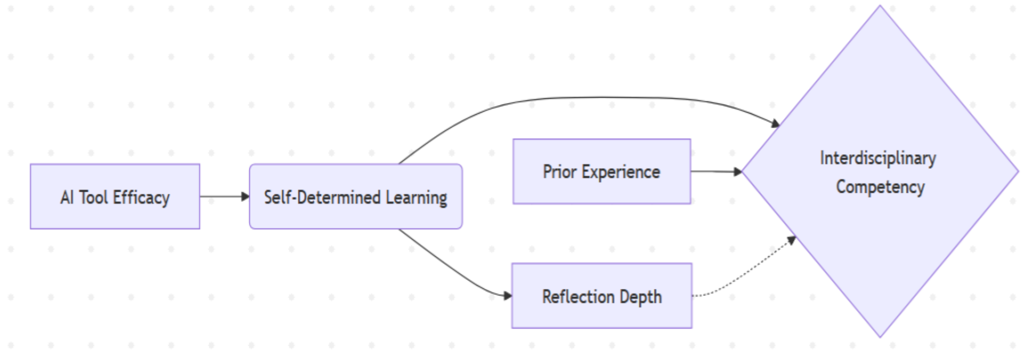

Figure 1. Hypothesized SEM Path Model

Conclusions And Next Steps

This position paper proposes a heutagogy-informed DBR framework for designing AI-enhanced learning environments that empower adult learners to tackle complex interdisciplinary problems. Grounded in self-determined learning, transformative reflection, and systemic analysis (activity theory), the framework guides the co-design of ethical AI tools (e.g., NASE, TJA, CDPM, BAFG) to foster autonomy, critical thinking, and real-world problem-solving. The next step involves implementing the three-phase DBR cycle across diverse adult education programs in China. We will iteratively test and refine the framework and tools through mixed-methods data collection (performance metrics, interviews, journals, activity theory mapping), aiming to generate validated design principles and practical guidelines for educators and designers.

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