Education Insights

Article

From Tool-Using to Collaborative Partnership: A Maturity Model and System Design Framework for Human-AI Interaction in Open University English Education

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Abstract: The integration of Generative AI (GenAI) into educational software systems is reshaping the human-computer interaction (HCI) landscape within intelligent tutoring systems and learning management systems. This paper investigates the interaction patterns between open university English teachers and AI-powered educational applications, examining the transition from a "tool-using" paradigm to a "collaborative partnership" model. Drawing on a mixed-methods study involving 108 teachers from central China, we analyze the current state, key dimensions, and system-level enablers of effective human-AI collaboration. Our findings reveal that while basic AI functionalities (e.g., content generation, grammar checking) are widely adopted, deep collaborative features (e.g., data-informed decision-making, pedagogical co-design) remain underutilized. We identify four critical system design dimensions—Interactive Co-Design Interfaces, Data-Driven Analytics Dashboards, Ethical AI Stewardship Modules, and Affective Computing for User Resilience—and propose a developmental model for human-AI interaction maturity. Practical implications for next-generation educational software design are discussed. This study contributes empirical evidence on user behavior and system requirements for human-AI symbiosis in educational technology, HCI, and computer-assisted language learning.

Keywords: Human-Computer Interaction; AI-Assisted Teaching Systems; Educational Software; Generative AI; Intelligent Tutoring Systems; User Behavior Analysis

1. Introduction

The rapid proliferation of generative artificial intelligence (GenAI), particularly large language models (LLMs) like ChatGPT and GPT-4, has catalyzed a paradigm shift in the design and functionality of educational software systems [1]. In particular, the application of these models in higher education has drawn significant research attention [2]. In the context of open universities, where teaching and learning are inherently mediated by Learning Management Systems (LMS) and digital platforms, this shift is especially pronounced. English language instruction, traditionally reliant on static content and human-mediated feedback, is now being integrated with AI systems capable of dynamic content generation, adaptive dialogue simulation, and real-time learner analytics [3].

However, a critical challenge in computer application research is no longer whether AI can perform specific teaching tasks, but how users (teachers) interact with these intelligent systems and how these systems should be designed to foster effective collaboration rather than simple tool-use [4]. While significant research has focused on improving the underlying algorithms of LLMs, less attention has been paid to the human-computer interaction (HCI) aspects, specifically the cognitive and behavioral patterns of users as they co-evolve with these intelligent agents [5].

This study addresses this gap by focusing on the use of AI-powered educational applications by open university English teachers in China—a user group facing unique challenges: high student-teacher ratios, fragmented adult learning schedules, and a strong

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demand for vocational relevance. We ask:(1) What are the current interaction patterns and maturity levels of human-AI collaboration among open university English teachers?(2) What are the key system-level dimensions that influence the transition from a "tool-user" to a "collaborative partner" interaction model?(3) What system design principles and developmental strategies can facilitate this transition? Employing a mixed-methods design combining questionnaires and interviews, we analyze usage patterns and perceptions. We conclude with a phased developmental model and actionable recommendations for intelligent educational system design.

2. Literature Review

2.1. Human-Computer Interaction (HCI) in Educational Software

The evolution of HCI in education has moved from command-line interfaces to graphical user interfaces (GUIs), and now to intelligent user interfaces (IUIs) powered by AI [6]. Traditional frameworks like the Technology Acceptance Model (TAM) and TPACK focused on technology as a passive tool [7]. However, the emergence of GenAI as a proactive and generative agent necessitates a new interaction paradigm. Recent HCI research calls for a "relational" ontology, recognizing AI as a "quasi-other" that can influence user decisions and actions, moving beyond simple human-machine interaction to a form of human-AI collaboration [8].

2.2. Human-AI Symbiosis and Collaborative Systems

The concept of human-AI symbiosis, originally coined by Licklider (1960), has been revitalized in the context of intelligent systems to describe a mutual, complementary relationship where both human and machine contribute their distinctive intelligence [9]. In educational technology, this translates to systems that do not just automate tasks but actively participate in co-design and co-evaluation of learning experiences [10]. For instance, in language education, AI is viewed not just as a correction tool but as an "intelligent writing assistant" that co-evolves with the user [11]. However, empirical research on how users interact with and internalize these collaborative systems remains scarce, particularly in open and distance education settings.

2.3. AI in Open and Distance Education Systems

Open universities are intensive ICT users, relying on LMS and online delivery [12]. AI integration enhances system intelligence by automating routine tasks, freeing teachers for higher-order interaction. But poorly designed systems may threaten user agency, causing anxiety and resistance [13]. Recent studies (2023–2025) stress "AI literacy" and transparency beyond operational skills to include ethical judgment and collaborative decision-making [14]. Researchers also call for system transparency and user education to support effective collaboration [15]. However, systematic empirical research on specific interaction patterns and system design requirements in this context is lacking.

2.4. Research Gap

Existing literature provides generic frameworks for digital competence and AI literacy but lacks (a) empirical analysis of specific interaction patterns between teachers and AI systems, (b) focus on user-behavior data to inform system design, and (c) a contextualized developmental model for human-AI collaboration maturity. This study aims to fill these gaps by empirically investigating the dimensions and current state of human-AI interaction in open university English education.

2.5. Comparative Analysis of Mainstream HCI Maturity Models

To contextualise our proposed HAIM (Human-AI Interaction Maturity) model, we compare it with three established frameworks in Table 1. HAIM contributes (a) education-specific co-design as a core dimension, (b) integration of ethical awareness and affective resilience, and (c) actionable design principles rather than mere descriptive stages.

Table 1. Comparison of the HAIM Model With Three Established Frameworks.

Model	Source	Core dimensions	Stages	Application	Relevance
Technology Acceptance Model (TAM)	Davis, 1989	usefulness, ease of use	No stage (continuous)	Predicting adoption intention	Baseline; ignores interaction depth
Human-Trust Development Model	Hoff & Bashir, 2015	Dispositional, situational, learned trust	Initial → Formation → Dynamic calibration	Automation trust	Informs trust aspect
Human-AI Collaboration Maturity	Ren et al., 2024	Transparency, explainability, adaptability	Tool → Assistant → Teammate → Coach	Medical AI decision support	Close but not education-tailored
HAIM (this study)	This paper	Co-design, data-driven, ethics, affect	Initial (Tool) → Managed (Analysis) → Defined (Collaborative)	AI-assisted educational software	Situated in CALL and educational HCI

3. Methodology

3.1. Research Design

This study employed a convergent parallel mixed-methods design. Quantitative data on user behavior and interaction patterns were collected via a structured questionnaire. Qualitative data on user experience and perceptions were collected through semi-structured interviews. The integration of data provides a holistic understanding of the human-AI interaction ecosystem.

3.2. Participants

Questionnaires were distributed to English teachers from four open university branches in Hubei, China. Of 120 sent, 108 valid responses were returned (90% response rate). Respondents: 68 female (63.0%), 40 male (37.0%); teaching experience 2–28 years (mean=11.4); 72% held master's or above. For interviews, we employed stratified purposive sampling to select 24 teachers (expanded from 12) based on AI usage frequency (high/low), experience (≥10/<10 years), and self-rated interaction maturity (high/low), with 6 per stratum. Saturation reached after 22 interviews; two additional confirmed no new themes. Interviews lasted 40–60 min, audio-recorded and transcribed.

3.3. Instruments

Questionnaire: A 32-item instrument was developed based on literature and prior research on technology acceptance and user interaction. It comprised four sections: (a) Demographics; (b) AI Usage Frequency and Purposes (6 items, 5-point Likert); (c) Perceived Interaction Dimensions (15 items, 5-point Likert) covering pedagogical co-design, data interpretation, ethical awareness, and emotional readiness; (d) Perceived barriers and support needs. The questionnaire was pilot-tested with 20 teachers. Cronbach's α for the main scale was 0.87.

Interview Protocol: Semi-structured interviews explored experiences, perceived role changes, emotional responses, and future expectations.

3.4. Data Analysis

Quantitative data were analysed using SPSS 26.0 (descriptive statistics, t-tests). Qualitative data were thematically analysed, with two researchers independently coding and reaching consensus.

4. Findings

4.1. Current State of AI Usage and Perceived Interaction

Usage Frequency and Purposes are summarised in Table 2. Only 23.1% of teachers reported using AI tools at least weekly; the majority (54.6%) used them occasionally, and 22.3% rarely or never. The most common purposes were content generation (67.6%) and grammar checking (61.1%), while advanced uses such as personalised feedback (29.6%) and learner analytics (18.5%) remained low. Usage frequency and purposes are summarised in Table 2. Only 23.1% used AI weekly; most (54.6%) occasionally; 22.3% rarely/never. Common uses were content generation (67.6%) and grammar checking (61.1%); advanced uses like personalised feedback (29.6%) and learner analytics (18.5%) remained low. Self-perceived interaction orientation (1=tool user, 5=fully collaborative) averaged 2.67 (SD=0.94). Only 14.8% rated ≥4, confirming a predominant tool-user pattern.

Table 2. Frequency and Primary Purposes of AI Tool Usage (N=108)

Usage frequency	% of teachers	Primary purpose (multiple choice)	% of teachers
Weekly or more	23.1%	Generating teaching materials	67.6%
Occasionally	54.6%	Grammar/spelling checking	61.1%
Rarely or never	22.3%	Designing exercises	48.1%
		Providing personalised feedback	29.6%
		Learner analytics	18.5%

4.2. Key Dimensions of Human-AI Interaction

Exploratory factor analysis on the 15 identity items yielded four distinct factors (eigenvalues >1.0, 68.3% variance explained), interpreted as critical system design dimensions (Table 3). Correlations among dimensions were moderate (r=0.32–0.48, p<0.01), indicating related but distinct facets.

Table 3. Descriptive Statistics of the Four Interaction Dimensions

Dimension	Mean (M)	SD
Pedagogical Co-Design (PCD) – co-planning and adjusting activities with AI	2.89	0.87
Data-Informed Dashboard (DID) – using AI-generated data for pedagogical decisions	2.52	0.92
Ethical AI Stewardship (AES) – addressing bias, privacy, and integrity	3.14	0.88
Affective-Emotional Resilience (AER) – confidence and human connection	2.98	0.91

4.3. Group Differences

Teachers with more than 10 years of experience scored significantly lower on PCD (M = 2.63 vs. 3.12, t = -3.04, p = 0.003) and DID (M = 2.31 vs. 2.78, t = -2.78, p = 0.006) compared to those with less experience. However, they scored higher on AES (M = 3.32 vs. 2.95, t = 2.41, p = 0.018). Teachers who had participated in AI-related training reported significantly higher scores across all dimensions, highlighting the importance of user education for system adoption.

4.4. Qualitative Themes from Interviews

Thematic analysis of 24 interviews revealed four overarching themes:

Theme 1: System Transparency and Trust – Users demanded explanations for AI outputs. T07 (female, 22 yrs): "If I don't understand why it suggests something, I can't fully trust it."

Theme 2: From 'Automation' to 'Augmentation' – Most viewed AI as a routine assistant, but a few described experiences where non-standard outputs challenged their thinking. T03 (male, 8 yrs): "The system expanded my perspective; it felt like a conversation."

Theme 3: User Interface and Workflow Integration –Enablers included seamless LMS integration, intuitive interfaces, and reflective features. Barriers were complexity, lack of integration, and no collaborative workflow support.

Theme 4: Tension Between System Autonomy and Human Control – High-frequency user T18 (male, 5 yrs): "I want proactive recommendations, but sometimes it's too proactive and disrupts my plan." This highlights the need to balance proactivity with user agency, aligning with intermediate automation principles.

5. Discussion

5.1. Interpreting the Findings: System Design for Collaborative Maturity

Our findings reveal that open university English teachers are primarily engaging with AI systems at a low-interaction maturity level, characterized by basic tool use. The high usage of "generating materials" and "grammar checking" versus the low usage of "learner analytics" and "personalized feedback" indicates that current systems are primarily used for automation, not augmentation.

This reinforces the need for a developmental model for Human-AI Interaction Maturity (HAIM), analogous to the Capability Maturity Model (CMM):

Phase 1: Initial (Tool Use): System is used for simple, routine tasks. User interaction is superficial.

Phase 2: Managed (Analysis & Reflection): System provides data and analytics, prompting user reflection and targeted experimentation. Workflows begin to integrate system outputs.

Phase 3: Defined (Collaborative Integration): System and user engage in a co-evolutionary process, co-designing and co-evaluating. System is seamlessly integrated into the user's professional practice.

Our cross-sectional data suggests most participants are between Phase 1 and Phase 2. The lower scores on PCD and DID for experienced teachers indicate that prior habits can be a barrier to adopting new interaction paradigms, highlighting the need for systems that are intuitive and provide a clear "onboarding" process for all user groups.

5.2. Implications for System Design and Development

Our findings have several direct implications for the design of AI-assisted educational software:

Design for Explainability (XAI): Systems must incorporate transparent decision-making processes. This aligns with the call for "glass-box" AI, where the rationale behind suggestions is clearly displayed to build user trust (Theme 1).

Develop Interactive Co-Design Modules: Rather than a one-way output (teacher asks, AI responds), systems should support multi-turn, collaborative dialogue (Theme 2). This requires the development of more sophisticated dialogue management systems.

Integrate Data-Driven Dashboards: Presenting complex learner data in an intuitive, actionable format is crucial (Dimension 2). System designers should prioritize information visualization and visual analytics to support data-informed decision-making.

Incorporate Affective Computing: Systems should not only process tasks but also recognize and support user emotional states (Dimension 4). This involves designing interfaces that reduce anxiety and promote a sense of control, possibly through gamified onboarding or personalized support agents.

5.3. Limitations and Future Research

This study is regionally bounded (central China), and findings may not be generalizable to other cultural or institutional contexts. The cross-sectional design cannot capture the longitudinal dynamics of interaction change. Future research could employ longitudinal data collection or design-based research (DBR) to track interaction patterns and test the efficacy of new system features in real-world settings. Comparative studies across different educational software platforms would also enrich the understanding.

6. Conclusion

This paper empirically examined user interaction patterns and system design requirements for fostering a transition from tool use to collaborative partnership in human-AI symbiosis within open university English education. Through a mixed-methods study of 108 teachers, we identified four critical system design dimensions: Pedagogical Co-Design Interfaces, Data-Informed Analytics Dashboards, Ethical AI Stewardship Modules, and Affective-Emotional Resilience. Our results reveal that most users remain in an early transitional stage, hindered by lack of transparency, limited integration, and insufficient collaborative features. We proposed a phased developmental model (HAIM) and actionable design principles. As AI evolves, designing systems that foster a collaborative mindset will be paramount to empowering educators to be more effective, creative, and human-centred.

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