ISSN 2522-6398 Vol. 8, Issue 12: 59-63, DOI: 10.25236/FER.2025.081209

Constructing a Core Competency Model for Postgraduate Students in Human–AI Collaborative Contexts

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Abstract: *The rapid advancement of artificial intelligence is profoundly reshaping postgraduate education. Beyond mastering disciplinary knowledge, cultivating graduates capable of effective human–AI collaboration has become an essential goal of talent development. To address this emerging demand, this study conducts a systematic review of domestic and international research on postgraduate education and human–AI collaboration and proposes a four-dimensional core competency model comprising AI Tool Mastery, Higher-Order Cognitive Construction, Human–AI Social Collaboration, and Value-Oriented Ethical Agency. The Analytic Hierarchy Process (AHP) is further employed to determine the relative weights of these dimensions. The findings aim to offer theoretical insights and practical guidance for promoting the high-quality development of postgraduate education in the era of artificial intelligence.*

Keywords: *Human–AI Collaboration, Postgraduate Education, Core Competencies, Model Construction, Analytic Hierarchy Process (AHP)*

1. Introduction

The rapid advancement of generative artificial intelligence has brought profound changes to postgraduate education. The human–machine relationship is shifting from traditional "tool use" to "intelligent collaboration," and postgraduate students are evolving from passive recipients of knowledge into "collaborative agents" capable of mobilizing AI systems for creation and co-working. This transformation challenges existing understandings of postgraduate core competencies. As mnemonic knowledge and procedural skills are increasingly augmented—or even replaced—by AI technologies[1], higher-order human strengths such as logical reasoning, critical thinking, and value judgment have become more crucial than ever[2, 3].

While existing studies offer valuable insights, many remain confined to theoretical argumentation regarding the necessity of educational paradigm shifts[4]. Others focus on isolated abilities—such as digital literacy or computational thinking[5]—yet lack a comprehensive and integrated competency framework. To date, no postgraduate core competency model has successfully integrated empirical grounding, technological logic, educational principles, and holistic human development while achieving cross-disciplinary consensus. The absence of such a model has led to fragmented competency lists that provide limited guidance for systematic educational reform. Moreover, existing theoretical models often lack the empirical evidence needed to address the complex demands of real-world human–AI collaborative contexts.

To bridge this gap, the present study constructs a theoretical framework through comprehensive literature analysis, synthesizes expert consensus using the Delphi method, and employs the Analytic Hierarchy Process (AHP) to determine the relative weights of competency dimensions. The resulting model conceptualizes the core competencies required of postgraduate students in human–AI collaborative environments. This study contributes to competence theory and AI-enhanced talent development while offering a theoretically grounded and practically actionable framework to support institutions in refining training objectives, optimizing curricula, and innovating teaching and assessment practices.

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2. Construction of the Core Competency Model for Postgraduate Students in Human–AI Collaboration

2.1 Model Construction Process

Drawing on Distributed Cognition Theory[6], this study systematically examines the core competencies required in human–AI collaborative contexts. Through an extensive review of domestic and international literature, an initial framework comprising four primary dimensions and twelve secondary indicators was developed. To ensure scientific rigor and reliability, two rounds of Delphi consultation were conducted with 21 senior experts from education, AI technology, and industry. The average expert authority coefficient was 0.85, with all individual coefficients above the acceptable threshold of 0.7. Recovery rates for the two rounds were 95.2% and 100%, indicating strong expert engagement and overall reliability.

Expert feedback informed several revisions: “multitasking ability” was removed; “algorithmic thinking” was incorporated into “AI tool mastery”; and “intercultural understanding” was merged into “human–AI social collaboration.” The coordination coefficient increased significantly from 0.386 to 0.512 ($p < 0.01$), demonstrating growing convergence among expert opinions and strong reliability of the finalized model.

2.2 Model Definition and Interpretation

Following the above procedures, the final core competency model for postgraduate students in human–AI collaboration was established, as shown in Figure 1.

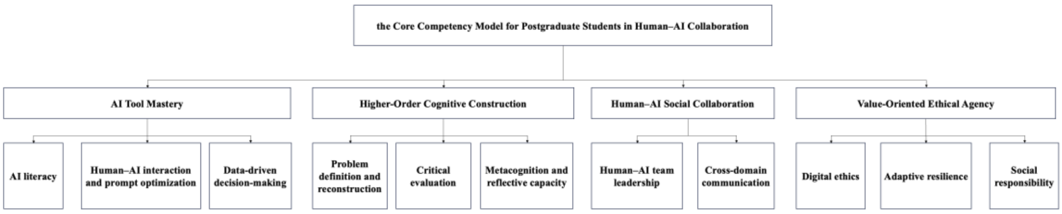

Figure 1. The Core Competency Model for Postgraduate Students in Human–AI Collaboration.

AI Tool Mastery refers to the foundational competencies enabling postgraduate students to accurately understand and effectively utilize AI technologies. It comprises three elements:

AI literacy, which involves understanding the basic principles and applications of AI and evaluating its appropriateness in specific contexts[7];

Human–AI interaction and prompt optimization, which entails improving interaction strategies and prompt design to enhance collaborative performance[8];

Data-driven decision-making, which focuses on collecting, processing, and analyzing data via AI tools to support scientific decision-making.

These components jointly form the foundational layer of human–AI collaboration.

Higher-Order Cognitive Construction denotes the essential abilities that allow postgraduate students to maintain and cultivate uniquely human strengths within human–AI collaborative environments[9]. It includes: Problem definition and reconstruction, the capacity to identify core issues in complex contexts and decompose them into actionable tasks; Critical evaluation, the ability to assess AI-generated content in terms of accuracy and logical coherence and to integrate human and machine inputs for decision-making; Metacognition and reflective capacity, referring to the continuous monitoring and optimization of one’s cognitive processes and human–AI collaboration strategies to achieve iterative cognitive development.

Human–AI Social Collaboration extends collaboration effectiveness from the individual level to team and societal levels. It consists of Human–AI team leadership, the ability to organize and coordinate hybrid teams composed of humans and AI agents to generate synergistic outcomes[10]; Cross-domain communication, the capacity to promote effective understanding and interaction among humans, AI systems, and external environments within interdisciplinary and multi-domain contexts[11].

Value-Oriented Ethical Agency represents the internalized value system and ethical awareness

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guiding postgraduate students to ensure that technological development serves the public good. It encompasses: Digital ethics, which includes adherence to principles of respect, fairness, and justice, and the protection of human dignity and agency; Adaptive resilience, the capacity to remain open-minded and continuously update one's knowledge amid rapid technological change; Social responsibility, which involves recognizing the societal implications of technology and leveraging human–AI collaboration to address real-world challenges and promote responsible innovation.

3. AHP Analysis of Core Competencies for Human–AI Collaboration

3.1 Establishment of the Hierarchical Structure

Based on the competency model developed above, an AHP hierarchical structure was constructed, as presented in Table 1. This structure includes the goal level (A), criterion level (B1–B4), and indicator level (C1–C11), illustrating the hierarchical relationships among competency components.

Table 1. Hierarchical Structure of the AHP Model.

Goal Level	Criterion Level	Indicator Level
Core Competencies for Postgraduate Human–AI Collaboration (A)	AI Tool Mastery (B1)	AI Literacy (C1)
		Human–AI Interaction Optimization (C2)
		Data-Driven Decision-Making (C3)
	Higher-Order Cognitive Construction (B2)	Problem Definition and Reconstruction (C4)
		Critical Evaluation (C5)
		Metacognition and Reflection (C6)
	Human–AI Social Collaboration (B3)	Human–AI Team Leadership (C7)
		Cross-Domain Communication (C8)
	Value-Oriented Ethical Agency (B4)	Digital Ethics (C9)
		Adaptive Resilience (C10)
		Social Responsibility (C11)

3.2 Weight Calculation

The 21 experts previously consulted were invited to conduct pairwise comparisons of factors at the same hierarchical level using a five-point scale. Excel was used for consistency testing, and all consistency ratios (CR) were below 0.1, indicating valid results. Subsequently, the geometric mean method was applied to aggregate all valid expert matrices into a group decision-making matrix.

Taking the comparison matrix of the criterion level (B) relative to the goal level (A) as an example, the aggregated matrix is presented in Table 2. The resulting weight vector was: W_1 = (0.1958, 0.3934, 0.1098, 0.3009) ^{T}, with λmax = 4.021, CI = 0.007, RI = 0.89, and CR = 0.0078 < 0.10, indicating satisfactory consistency. The ranking of the four primary dimensions is: Higher-Order Cognitive Construction (B2) > Value-Oriented Ethical Agency (B4) > AI Tool Mastery (B1) > Human–AI Social Collaboration (B3).

Table 2. A–B Judgment Matrix

A	B1	B2	B3	B4
B1	1	1/2	2	1
B2	2	1	3	2
B3	1/2	1/3	1	1/2
B4	1	1/2	2	1

Using the same procedure, the comprehensive weights of the eleven secondary indicators were calculated as: w = (0.0643, 0.1168, 0.0509, 0.2123, 0.1334, 0.0509, 0.0896, 0.0693, 0.2268, 0.0366, 0.0622) ^{T}.The ranking is: Digital Ethics (C9) > Problem Definition and Reconstruction (C4) > Critical Evaluation (C5) > Human–AI Interaction Optimization (C2) > Human–AI Team Leadership (C7) > Cross-Domain Communication (C8) > AI Literacy (C1) > Social Responsibility (C11) > Data-Driven Decision-Making (C3) = Metacognition and Reflection (C6) > Adaptive Resilience (C10).

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3.3 Analysis of Weight Results

The results show that Digital Ethics (C9) ranks first with a weight of 0.2268, while Problem Definition and Reconstruction (C4) and Critical Evaluation (C5) together account for 0.3457. This indicates that value-oriented ethical reasoning and higher-order cognition jointly form the core pillars of the competency model. As AI increasingly performs basic information-processing tasks, postgraduate education must prioritize cultivating the ability to precisely formulate complex problems and critically evaluate AI outputs. Meanwhile, ethical consciousness is essential for ensuring responsible technological application and preventing innovation-related risks.

At the operational level, Human–AI Interaction Optimization (C2), Human–AI Team Leadership (C7), and Cross-Domain Communication (C8) rank fourth, fifth, and sixth respectively, each exceeding 0.065. This suggests that effective human–AI collaboration requires not only proficiency in AI tool use but also the ability to optimize interaction processes, lead hybrid teams, and collaborate across specialties.

By contrast, Social Responsibility (C11)—although important—is positioned eighth, indicating that it should be viewed as an applied extension of digital ethics rather than a standalone top-tier element. Data-Driven Decision-Making (C3) and Metacognition and Reflection (C6) have lower and identical weights, implying that experts may regard them as implicit supporting abilities whose value is expressed through more externally observable competencies such as critical evaluation. The lowest weight assigned to Adaptive Resilience (C10) suggests that educational priorities should emphasize cultivating the ability to define, critique, and lead—rather than merely adapting to—technological change.

4. Conclusion and Future Directions

4.1 Research Conclusions and Recommendations

Through systematic theoretical construction and AHP-based empirical analysis, this study draws three key conclusions.

First, the competency model for human–AI collaboration comprises four interrelated dimensions: AI Tool Mastery, Higher-Order Cognitive Construction, Human–AI Social Collaboration, and Value-Oriented Ethical Agency.

Second, weight analysis empirically demonstrates that Value-Oriented Ethical Agency and Higher-Order Cognitive Construction constitute the model's core pillars. Among all indicators, Digital Ethics (C9) has the highest weight, followed by Problem Definition and Reconstruction (C4) and Critical Evaluation (C5), underscoring the decisive role of ethical guidance and higher-order thinking in shaping human–AI collaboration competencies.

Third, at the practical level, Interaction Optimization, Team Leadership, and Cross-Domain Communication are the key operational skills enabling efficient collaboration; meanwhile, Digital Ethics serves as the normative foundation for ensuring that technological practices align with societal values, and Social Responsibility reflects the application of these ethics in real contexts.

To systematically cultivate these competencies, a multi-stakeholder educational ecosystem is required. Policymakers should strengthen top-level design by integrating core competencies into quality assurance systems and issuing ethical guidelines. Universities should reform curricula and pedagogies by developing project-based courses focused on problem definition, critical evaluation, and interaction optimization. Teachers should enhance their instructional capacity to guide human–AI collaborative processes. Postgraduate students should transition from passive tool users to proactive collaboration leaders, internalizing digital ethics and refining higher-order cognitive skills in research practice.

4.2 Limitations and Future Research

Despite establishing a core competency model and clarifying weight relationships, this study faces several limitations. First, although the Delphi experts and AHP evaluators represent education, technology, and industry, the sample size remains limited; future studies should expand the expert pool to enhance generalizability. Second, because the model is based on expert consensus, its validity and applicability require further verification through large-scale empirical studies in authentic educational settings.

Future research may proceed in three directions: First, developing standardized assessment tools

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based on this model to diagnose the human–AI collaboration competencies of postgraduate students across disciplines; Second, conducting educational action research to integrate the model into curriculum, instruction, and evaluation systems, followed by longitudinal outcome tracking; Third, conducting cross-cultural comparative studies to explore how technological and sociocultural differences shape competency requirements, thereby informing both internationalization and contextualization of postgraduate education in China.

Acknowledgements

This work was supported by the 2025 Hubei Provincial Education Science Planning Project (Grant No. 2025GA085), the Graduate Education Quality Project of Hubei University of Automotive Technology (Grant No. Y202515, Y202417), and the Teaching Research and Reform Project (Innovation and Entrepreneurship Education Special Program) of Hubei University of Automotive Technology (Grant No. SCJY202403), 2025 Higher Education Science Research Planning Program of the China Association of Higher Education (Grant No. 25DF0201).

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