Theoretical Exploration of Competency Model Construction for AI-Empowered Human Resource Management Roles

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Abstract: The rapid advancement of artificial intelligence (AI) technologies is fundamentally transforming the theoretical foundations and practical paradigms of human resource management (HRM). Anchored in traditional competency theory and informed by the evolving influence of technological change on HRM, this paper undertakes a theoretical exploration of constructing HR competency models under AI-empowered conditions. Through literature review and conceptual deduction, the study finds that the integration of AI has led to a structural shift in required HR competencies: conventional transactional capabilities are being supplanted by technological application competency, data analytical competency, strategic thinking competency and interpersonal interaction competency. These dimensions constitute the core competencies for HR professionals in the AI era. The proposed Four-Dimensional Competency Model offers a theoretical framework for cultivating and developing HR talent under digital transformation conditions, thereby enriching the practical application of competency theory in the digital age.

Keywords: Artificial Intelligence; Human Resource Management; Competency Model; AI-Empowered;

1. Introduction

With the rapid development of artificial intelligence (AI) technologies, a new form of productive capacity is emerging as a key driver of societal transformation. AI not only reshapes traditional modes of production but also exerts profound influence on organizational management and the field of human resource management (HRM). According to a McKinsey survey employees now spend approximately 70% of their working hours engaging with AI or other intelligent technologies [1]. The integration of smart technologies affects not only the nature and mode of work but also fundamentally alters the definition and requirements of job competencies.

Traditional competency models were predominantly built upon relatively stable work environments and clearly defined functional divisions, emphasizing administrative management, interpersonal communication, and process execution capabilities. However, the advent of AI has disrupted this stability, rendering conventional frameworks inadequate for addressing the demands of emerging work paradigms. Consequently, the construction of competency models adapted to the AI era has become a critical issue in both theoretical research and practical exploration.

Simultaneously, academic programs in HRM-particularly within universities-are under increasing pressure to transform. Talent development must dynamically align with evolving industry needs. Within this context of "AI-empowered HRM," building scientifically grounded competency frameworks not only carries significant theoretical implications but also provides tangible value for higher education institutions and professional career development.

2. Literature Review and Theoretical Foundations

2.1 Evolutionary Trajectory of Competency Theory

McClelland [2] first introduced the concept of competency, challenging the validity of traditional intelligence testing and academic performance assessments. He defined competency as "individual traits that distinguish performance levels within specific job roles and organizational environments," and proposed the initial Iceberg Model, which emphasized the identification and performanceoriented nature of competencies. Building upon this, Boyatzis [3] defined competency as "the underlying characteristics possessed by individuals that result in effective or superior job performance," highlighting the latent nature and causal mechanisms of competencies. His model encompasses six dimensions: goal and action management, leadership, human resource management, guidance of subordinates, concern for others, and professional knowledge. This framework's key contribution lies in its contextual linkage of competencies to management scenarios and its emphasis on functional attributes. Spencer synthesized prior theories and enriched the Iceberg Model by categorizing competencies into observable surface-level elements (knowledge and skills) and hidden deep-level traits (social role, self-concept, traits, and motivation). They developed a comprehensive Competency Dictionary, which elucidated the hierarchical structure of competencies, stressed the importance of deep-level attributes, and provided systematic assessment tools.

Since the turn of the 21st century, competency theory has evolved along three major trajectories:

(1) Contextualization Shift: Scholars increasingly recognize that competencies are context-bound manifestations shaped by organizational culture and task demands. For instance, Shippmann et al. [4] proposed a contextualized competency model, emphasizing the need to tailor competency standards to specific settings.

(2) Dynamic Development: Traditional competency models assume relative stability in skill requirements, an assumption rendered obsolete by rapid change. Athey and Orth [5] introduced the concept of "future competencies," underscoring the importance of forecasting and cultivating capabilities needed for emerging roles.

(3) Integrative Perspective: Competencies are now viewed as outcomes of multilevel interactions among individuals, teams, and organizations. Sanchez and Levine [6] proposed a multilayered competency framework integrating individual, team, and organizational competencies.

In organizational practice, competency models are typically categorized into three domains:

(1) Core Competencies: Reflecting organizational DNA—such as integrity, innovation, and customer orientation—and are applicable to all employees.

(2) Generic Competencies: Including communication, collaboration, and learning—relevant to most positions but context-dependent.

(3) Technical/Professional Competencies: Representing position-specific skill sets and domain expertise such as data analysis and project management.

Model construction should emphasize job differentiation and adhere to principles of simplicity, pragmatism, layered customization, measurability, and actionable utility—ensuring alignment with strategic imperatives and seamless integration into recruitment, performance appraisal, and training processes.

2.2 Current Applications of AI in the Human Resources Domain

Existing research and practical experience reveal that the applications of artificial intelligence (AI) in the field of human resource management (HRM) predominantly concentrate on the following areas:

(1) Recruitment and Selection: Intelligent resume screening, algorithmic job-person matching, video interview analytics, and the development of talent profiles.

(2) Training and Development: Personalized learning recommendations, smart curriculum design, predictive analysis of learning outcomes, and career development planning [7].

(3) Performance Management: Real-time performance monitoring, multidimensional data analytics, performance forecasting models, and intelligent feedback systems.

(4) Employee Relations: Sentiment analysis, attrition prediction, employee experience optimization, and AI-driven Q&A support [8].

(5) Compensation and Benefits: Market-based compensation analysis, structural optimization of pay systems, and personalized benefits allocation [9].

AI influences HR practice through three primary mechanisms:

(1) Automation: Streamlining repetitive and rule-based tasks to enhance operational efficiency and reduce human error.

(2) Augmentation: Leveraging data analytics and pattern recognition to bolster HR insights and decision-making quality.

(3) Transformation: Innovating new modes of work and value creation, such as predictive

talent management and personalized employee experience strategies.

2.3 Methodologies for Competency Model Construction

Competency model development encompasses a range of methodological approaches [10], including:

(1) Behavioral Event Interview (BEI): Conducting in-depth interviews with high-performing and low-performing individuals to extract key behavioral indicators influencing performance. Particularly effective for identifying core traits from the bottom up.

(2) Survey Method: Utilizing standardized competency dictionaries to solicit organization-wide input and identify the most critical attributes.

(3) Benchmarking: Adapting models from leading industry organizations while contextualizing them to the specific conditions of the focal enterprise.

(4) Strategic Derivation: Deconstructing enterprise-level strategic goals to distill requisite competencies, refined further in accordance with position-specific requirements.

(5) Expert Panel Discussion: Synthesizing interdisciplinary insights to improve the scientific rigor and applicability of the model.

In practice, model construction typically integrates multiple methods. A common sequence involves strategic derivation, followed by BEI interviews and survey collection, culminating in expert deliberation to formulate a competency indicator system that is both strategically aligned and position-sensitive.

3. Applications of Artificial Intelligence in Job Analysis and Competency Modeling

3.1 Intelligent Transformation of Job Analysis Driven by AI

Traditional job analysis methods have heavily relied on manual processes such as interviews, surveys, and direct observation. These approaches are typically time-consuming, lack precision, and suffer from poor reproducibility. The advent of AI-particularly technologies like NLP, semantic understanding, and large-scale language models—has ushered in a new paradigm in job analysis. These technologies enable the automatic parsing of job descriptions and responsibilities, structuring large volumes of job data, and generating standardized templates based on industry-specific knowledge graphs. As a result, analysis efficiency has increased exponentially, and content recommendations have become more accurate and consistent.

Contemporary AI-driven job analysis procedures typically involve the following stages:

(1) Automated Data Collection: Extracting information from internal job descriptions, operational documents, and external recruitment advertisements.

(2) NLP-Based Duty Extraction: Identifying keywords and behavioral indicators to automatically generate job responsibility lists and required competencies.

(3) Dynamic Feedback Integration: Incorporating performance metrics and user feedback to iteratively refine job profiles and produce adaptive "living documents" responsive to business evolution.

3.2 AI-Enabled Competency Library Construction and Management

AI technologies facilitate the extraction, classification, and hierarchical structuring of competency elements by triangulating data from high-performing employee behaviors, industry job specifications, and strategic organizational priorities. This process significantly improves both the systematic integrity and accuracy of competency repositories while ensuring continual updates and strategic alignment. Consequently, AI-enhanced competency libraries become more effective tools for organizational application.

Technically, a typical AI toolkit can provide three essential forms of support:

(1) NLP and Occupational Taxonomy: Employing natural language processing and standardized classification systems to perform intelligent categorization across industry, function, and job levels, thereby helping HR professionals identify core and specialized competency requirements.

(2) Big Data Benchmarking: Using external and internal performance data to detect frequently occurring, high-impact competencies and build predictive competency structures.

(3) Behavioral Cloud Analysis: Applying behavioral science techniques to mine task-based behavioral patterns and translate them into standardized competency descriptors and proficiency levels, enhancing the model's

evaluative clarity and measurability.

An AI-empowered competency repository enables rapid retrieval of role-specific skills and facilitates seamless linkage between job descriptions and talent assessment tools. This approach elevates the scientific rigor, operational practicality, and implementation efficiency of model construction, offering robust technical support for precise, scalable, and sustainable talent selection and development frameworks.

3.3 Algorithmic Applications in Person-Job Matching and Competency Assessment

The infusion of AI into recruitment and evaluation processes substantially enhances the accuracy of person-job matching and the scientific validity of competency assessments. NLP-powered systems automatically extract key skills, work experiences, and educational qualifications from candidates' resumes and semantically compare them against job descriptions to deliver high-precision matching recommendations. This automated mechanism increases recruitment efficiency and mitigates bias caused by human judgment errors.

During interviews, AI technologies further contribute by leveraging multimodal recognition capabilities-including voice analysis, video image processing, micro-expression decoding, sentiment modeling, and cognitive trait assessments-to conduct comprehensive candidate evaluations. These systems generate job-fit analytics reports that minimize the impact of performative interviewing and strategic impression management, enabling more objective and nuanced assessments of candidate values and personality traits.

Moreover, AI supports the construction of holographic talent profiles, integrating cognitive ability, motivation, personality dimensions, organizational performance alignment, cultural fit, and developmental potential into a closed-loop data architecture. These profiles not only inform recruitment decisions but also guide promotions, role transitions, and targeted training, thereby enabling forward-looking talent management strategies.

4. Data-Driven Optimization and Dynamic Iteration of Competency Models

As enterprises undergo strategic restructuring, organizational transformation, and respond to evolving competitive landscapes, job functions and responsibilities are changing rapidly-rendering traditional competency models increasingly obsolete. Conventional approaches, often grounded in static data and subjective expertise, follow the "build once, use long-term" paradigm, overlooking the fluidity of role requirements and technological environments. Against the backdrop of digital transformation and organizational agility, competency models must now incorporate mechanisms for rapid response and structural adaptability. AI serves as a critical enabler in this optimization, offering tools for real-time organizational sensing, capability gap prediction, and structural recalibration to support dynamic model evolution.

4.1 Data-Driven Model Evaluation and Feedback Loop

Competency model refinement can be achieved through a closed-loop, data-driven process. This typically involves:

(1) Multi-Source Data Integration: Automatically aggregating performance metrics, training records, project outcomes, and attrition rates from HR and business platforms to build a robust evaluation foundation.

(2) Big Data Correlation Modeling: Identifying relationships between competencies and performance indicators to dynamically adjust competency weighting and enhance model alignment and effectiveness.

(3) Scheduled Iteration Cycles: Instituting quarterly or semi-annual review cycles to incorporate emerging business trends and revise competency items, thereby ensuring the model's agility and contextual relevance.

(4) Outcome-Based Feedback Mechanism: Tracking key performance outcomes-such as improved recruitment match rates and reduced turnover-to validate model effectiveness and refine future iteration paths, creating a cyclical improvement loop in competency management.

4.2 Agile Iteration and Contextual Adaptability of Models

Effective competency models must exhibit high agility and scenario responsiveness in real-world applications. Leveraging AI technologies, organizations can develop capability maps aligned to job families, functional tracks, and business contexts to intelligently match competencies and recommend updates.

During strategic pivots or product launches, the system can rapidly identify essential competencies and recommend enhancements.

In cases of organizational expansion or geographic diversification, models can automatically recalibrate competency frameworks to ensure cultural fit and regional relevancy.

This dynamic adaptability not only improves model scalability but also strengthens the organization's foresight in anticipating future competency demands.

4.3 Synergistic Enhancement of Organizational Capability through Model Iteration

A data-driven competency model is not merely a tool for talent management—it serves as a conduit for organizational capability evolution. During iterative cycles, enterprises can identify capability gaps, design personalized learning trajectories, and construct career development pathways that align individual growth with organizational advancement.

AI systems can continuously evaluate employee competency shifts, fostering targeted cultivation strategies. Simultaneously, organizations can harness capability maps and career trajectory analytics to optimize talent pipelines and strategic talent reserves. Thus, model optimization becomes a strategic alignment mechanism-providing theoretical foundations and practical frameworks for cultivating a competency-based competitive advantage.

5. Transformation of HR Practices in the Age of AI

5.1 Evolution of HR Work Content

(1) From Administrative Tasks to Strategic Involvement AI systems have taken over many routine HR functions-such as attendance tracking, payroll processing, and certificate generation-freeing HR professionals to engage in higher-order strategic activities like organizational design, culture building, and change management. The focus of HR work is shifting from "control" to "service," and from "management" to "enablement."

(2) From Intuition-Based Decisions to Data-Driven Insights AI offers powerful tools for data collection and analysis, enabling HR decisions to move away from reliance on subjective judgment and toward evidence-based insights. Applications such as talent profiling, turnover prediction, and performance analytics now require HR professionals to cultivate data literacy and analytical competencies, empowering them to identify patterns, validate hypotheses, and support decision-making with empirical evidence.

(3) From Standardization to Personalization AI makes large-scale personalization feasible. Employee learning paths, career development strategies, and benefit packages can be tailored to individual characteristics and needs. This calls for HR professionals to embrace the value of personalization, master design methodologies for customized solutions, and strike a balance between operational efficiency and personalized experience.

5.2 Shifting Competency Requirements for HR Professionals

(1) Technical Literacy as a Foundational Competency While HR professionals are not expected to be technical experts, a fundamental level of technical fluency has become essential. This includes: Understanding basic principles and application scenarios of AI technologies; Communicating effectively with technical teams; Maintaining awareness of data privacy and cybersecurity; Assessing the feasibility and risks of tech-enabled solutions.

(2) Human-AI Collaboration as a Core Capability The new HR paradigm emphasizes collaboration with AI rather than competition against it. HR professionals must learn to: Identify tasks suitable for automation versus those requiring human judgment; Design efficient workflows that leverage both human and AI strengths; Oversee the quality of AI outputs; Navigate the ethical complexities of human-AI interaction

(3) Continuous Learning as a Prerequisite for Success Rapid technological evolution demands that HR professionals maintain a state of perpetual learning. This goes beyond acquiring new tools—it entails embracing new ways of working, thinking, and creating value. Key traits include learning agility, knowledge integration capacity, and cross-disciplinary thinking.

6. Constructing the HR Competency Model in the Age of AI

6.1 Identification of Competency Elements

Based on theoretical analysis and logical deduction, this study identifies four core competency dimensions required of HR professionals in the AI era:

6.1.1 Technological Application Competency

Digital Tool Utilization: Proficient use of HR information systems, data analytics tools, and collaborative platforms.

(1) AI System Management: Understanding the functions and limitations of AI systems; ability to configure, monitor, and optimize AI applications.

(2) Technology Assessment: Capability to evaluate the applicability, cost-effectiveness, and implementation risks of various technological solutions.

(3) Technological Ethics Awareness: Awareness of ethical issues in AI applications and ensuring technological use complies with legal and moral standards.

6.1.2 Data Analytical Competency

Data Thinking: Ability to translate business problems into data questions and use data to validate hypotheses and support decisions.

(1) Statistical Analysis: Mastery of basic statistical methods and understanding of concepts such as data distribution, correlation, and significance.

(2) Visualization: Ability to convert complex data into intuitive charts and reports to effectively communicate insights.

(3) Predictive Modeling: Understanding of fundamental principles of predictive models and the ability to interpret and apply model results.

6.1.3 Strategic Thinking Competency

Business Acumen: Deep understanding of organizational strategies, business models, and value creation logic.

(1) Systems Thinking: Capability to analyze issues from a systemic perspective and recognize interrelationships among organizational elements.

(2) Foresight and Planning: Ability to anticipate technological and societal trends and develop forward-looking talent strategies.

(3) Change Management: Proficiency in driving organizational change and managing resistance and risks.

6.1.4 Interpersonal Interaction Competency

Emotional Intelligence: Capacity to understand and manage emotions—both one's own and others—to foster trust.

(1) Communication and Coordination: Effective communication with stakeholders from diverse backgrounds and coordination of interests.

(2) Coaching and Mentoring: Ability to support employee development, stimulate potential, and provide personalized guidance.

(3) Cultural Shaping: Understanding, transmitting, and cultivating organizational culture to create a positive work atmosphere.

6.2 Hierarchical Structure of the Competency Model

Drawing inspiration from the Iceberg Model, this study constructs a four-layer competency framework (Table1):

(1) Knowledge Layer (Surface Level) Includes foundational knowledge in AI (machine learning, natural language processing, computer vision), data science (statistics, data mining, data visualization), HR expertise (human resource management, labor laws, organizational behavior), and business domain knowledge (industry characteristics, business processes, competitive dynamics). These are relatively easy to acquire and update and serve as the foundation of competency.

(2) Skill Layer (Subsurface Level) Encompasses technical skills (using AI tools, system configuration, process automation), data analytical skills (data cleaning, statistical analysis, model interpretation), interpersonal coordination skills (negotiation, public speaking, conflict management, teamwork), and project management skills (project handling, change management, risk control). These skills are developed through practice and are expressions of knowledge in action.

(3) Value Layer (Deep Level) Comprises value orientations including:

Data-Driven: Belief in the power of data and evidence-based decision-making.

People-Centric: Respect for individual differences and attention to employee experience.

Continuous Innovation: Embracing change and courage to experiment.

Ethical Responsibility: Adherence to professional ethics and commitment to fairness and justice. These values influence behavioral choices and decision preferences.

(4) Trait Layer (Core Level) Refers to relatively stable personality traits, including:

Learning Agility: Ability to rapidly acquire new knowledge and skills.

Adaptability: Flexibility and openness when facing change.

Creativity: Ability to generate new ideas and solutions.

Empathy: Sensitivity to others' feelings and needs. These traits are critical differentiators of top performers.

Table 1. Hierarchical Structure of the Competency Model

Layer	Description
Knowledge Layer (Surface)	foundational knowledge in AI; data science; HR expertise; business domain knowledge
Skill Layer (Subsurface)	Encompasses technical skills; Data analytical skills; Interpersonal coordination skills; Project management abilities
Value Layer (Deep Level)	Data-Driven; People-Centric; Continuous Innovation; Ethical Responsibility
Trait Layer (Core Level)	Learning Agility; Adaptability; Creativity; Empathy

7. Implications and Future Directions

7.1 Practical Implications

For Organizations: Organizations should incorporate AI capability development into their HR strategic planning to systematically enhance the digital competencies of HR teams. Building a learning-oriented HR organization that fosters an environment conducive to technological learning and application is critical. Emphasis should also be placed on cultivating a culture of human-AI collaboration to prevent technology-induced anxiety and resistance.

For HR Professionals: HR practitioners are advised to proactively acquire knowledge and skills related to AI, though expertise in technology is not a prerequisite. The focus should be on cultivating those human-centric competencies that are difficult for AI to replicate-such as creative thinking, emotional intelligence, and ethical judgment. Maintaining learning agility and adaptability in fast-changing environments has become a vital professional attribute.

For Higher Education Institutions: Universities should update their HRM curricula to include AI technologies and data analytics. Pedagogical approaches should integrate theory with practical applications, offering real-world AI implementation scenarios. The overarching aim should be to foster holistic competencies in students rather than narrow technical skills.

7.2 Limitations and Future Research Prospects

This study remains conceptual in nature and lacks empirical validation. A fully operationalized competency model necessitates support from empirical data. Moreover, the theoretical framework as presented does not account for contextual contingencies-competency requirements may vary significantly across organizations differing in industry, scale, and cultural orientation.

Future research should focus on empirical testing of the proposed model, including cross-contextual comparison of competency structures to distill both universal and context-specific attributes. Ultimately, this will inform the development of standardized competency assessment tools tailored to HR roles in the AI era.

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