The Competency Speed Gap: How Artificial Intelligence Outpaces HR Generalists' Capability Development

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Abstract

The integration of artificial intelligence into human resource management practices has created an unprecedented temporal mismatch between the accelerating pace of competency obsolescence and the relatively fixed speed of traditional professional development mechanisms. This paper introduces the competency speed gap framework, a conceptual model that positions competency transformation as a temporal phenomenon, in which AI-induced obsolescence outpaces the ability of organizational learning systems to develop new capabilities among HR generalists. Drawing on the established theory of competency development and recent evidence on AI integration in HR functions, the goal of this paper is to propose a framework based on the summary of recent literature on the subject. The framework highlights the tendency of an exponentially growing distance: the phenomenon of structural asymmetry occurring between technology-driven and human learning cycles, as well as the multi-level impact of AI across individual, organizational, and systemic dimensions. The four theoretical predictions presented here address the topics of competency polarization, task-level transformation, hybrid collaboration models, and the primacy of organizational enablers. The paper concludes with six testable propositions that provide a basis for future quantitative research exploring the organizational conditions under which the competency speed gap tends to widen or narrow. This research adds a temporal perspective to recent degradation of skills, and emphasizes that the challenge is not a static skills gap but rather a dynamic speed difference that requires a basic reconsideration of organizational learning cycles, the infrastructure for professional development, and HR education.

Keywords: Artificial Intelligence, HR Generalists, Competency Speed Gap, Competency Obsolescence, Organizational Learning, AI-driven Change, Competency Development

Introduction

Artificial intelligence (AI) has evolved from a technological novelty into a pervasive force that is fundamentally reshaping professional practice across various occupational domains (Brynjolfsson, 2022; Russell & Norvig, 2022). Within Human Resource Management (HRM), AI systems progressively automate recruitment screening, enable predictive workforce analytics, and transform data analysis capabilities (McCartney et al., 2021; Zhang, 2023). This thus creating a phenomenon that this research refers to as the *competency speed gap*: the widening temporal disconnect between the accelerating pace of AI-induced competency obsolescence and the relatively fixed speed at which traditional professional development mechanisms can cultivate new capabilities.

Recent empirical evidence confirms that this transformation is already underway. A European Commission study (2023) examining algorithmic management across European Union (EU) member states found that between 0.7% and 21% of organizations are already using AI in HR functions such as recruitment, employee evaluation, and task allocation (European Commission, 2023, pp. 25-26). This widespread adoption provides the context for

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understanding the emergence of a competency speed gap: HR professionals must adapt to AI not only as a single technological change but also as a systemic transformation affecting multiple HR functions simultaneously.

This study aims to provide a conceptual framework that positions the transformation of competencies as a temporal phenomenon. Rather than conducting empirical research, this paper synthesizes existing literature to propose a framework for competency speed gap. This theoretical model captures the widening temporal disconnect between AI-driven competency obsolescence and traditional organizational learning cycles. The specific objectives of this paper are as follows.

5. To review and synthesize existing literature on the development of competencies, AI integration in HR and organizational learning in order to establish the theoretical foundations of the emerged competency speed gap.
6. To propose a conceptual framework that positions the competency speed gap as a multi-level, temporal phenomenon characterized by exponential divergence, structural asymmetry, and systemic impact.
7. To advance theoretical predictions as to how AI integration polarizes competency requirements, transforms task structures, necessitates hybrid collaboration models, and depends on organizational enablers rather than individual characteristics.
8. To formulate testable propositions for future quantitative research that examines the organizational conditions under which the competency speed gap may widen, narrow, or become manageable at organizational level.

The following section summarizes prior literature on competency development, the integration of AI in HR, and organizational learning systems to establish the theoretical background for the framework of competency speed gap.

Although the available literature has extensively explored the role of AI in certain HR functions – such as recruitment (Albassam, 2023; Black & Van Esch, 2020), analytics (McCartney et al., 2021) and process automation (Zhang, 2023) – and has addressed general conceptual issues in competency development (Boyatzis, 1991; McClelland, 1973; Spencer & Spencer, 1993), a critical gap persists. To the author's best knowledge, there is only a limited number of studies that have specifically addressed the temporal aspect of this phenomenon and examined whether the rate of AI-induced competency obsolescence (Allen & De Grip, 2012; Buttazzo, 2023) markedly exceeds the rate of organizational learning and professional development mechanisms (Kirkpatrick & Kirkpatrick, 2006; Kolb, 1984). Although there are international academic references to the shortening of the half-life of learned skills (Deming & Noray, 2020) and temporal asymmetries between technological change and organizational capacity (Bühler et al., 2022; Chuang et al., 2024), no comprehensive conceptual or empirical framework currently examines or addresses this accelerating speed differential, i.e. the competency speed gap specifically in the context of the HR generalist' roles (Bankins et al., 2024; Piwowar-Sulej et al., 2024).

This observation renders the present study both timely and necessary. Addressing this current research gap by reviewing prior literature on the theory of competency development (De Vos et al., 2011; Parry, 1996) and AI integration in HR (European Commission, 2023; Charlwood & Guenole, 2022), the study aims to establish a framework that views the transformation of competencies as a temporal phenomenon and offers propositions for further empirical investigation. The following question arises: *Through what mechanisms does AI generate a competency speed gap, that is, how does the temporal trajectory of HR generalists' competency development diverge from the speed of technological change and what organizational factors (Tracey et al., 1995; Ranasinghe et al., 2024) accelerate or decelerate this dynamic process?*

Literature Review

This paper adopts a narrative, theory-driven literature review strategy to support conceptual framework development in line with established guidance on narrative overviews of the literature (Green et al., 2006). The review started from seminal works in competency theory, learning theory and AI in HR, and then applied backward and forward citation tracking (snowballing) to identify additional relevant studies consistent with recent recommendations that citation tracking can usefully complement database searching (Hirt et al., 2023; Wohlin, 2014). The search focused on peer-reviewed journal articles, books and policy reports published primarily in English between 1980 and 2025 that address competency theory, AI integration in HR and organizational learning. Sources were identified through database searches (Web of Science, Scopus, Google Scholar) and citation chaining using combinations of keywords such as "competency development", "HR generalist", "artificial intelligence in HR", "skill obsolescence" and "organizational learning". Priority was given to highly cited foundational works and recent empirical or conceptual studies published in reputable journals. References were included if they directly informed the temporal dynamics of competency transformation or the multi-level impact of AI on HR roles, while purely technical AI studies without organizational or competency implications were excluded.

Building upon McClelland's (1973) fundamental concept, according to which competencies are viewed as clusters of knowledge, skills and attitudes correlating with job performance, and incorporating Dubois's (1998) reference to organizational context and environmental constraints, competency is defined here as an integrated set of knowledge, skills, behaviours, and cognitive capabilities that enable HR generalists to effectively perform their core tasks throughout the employee lifecycle and organizational functions. This definition recognizes competency as dynamic, measurable capabilities that manifest through successful task performance and must continuously adapt as organizational and technological environments change (Parry, 1996; McClelland, 1973).

This concept is consistent with broader traditions of competency theory. Boyatzis (1991) emphasizes that competencies represent "*characteristics underlying successful performance in a particular organizational role*" (p. 48). Spencer and Spencer (1993) further advance this framework by distinguishing between threshold competencies (minimum requirements for effective performance) and differentiating competencies (characteristics that distinguish superior performers). These theoretical foundations establish that competency is not static knowledge but a dynamic, context-dependent capability requiring continuous adaptation and development.

Following Caldwell's (2003) identification of multifaceted HR roles and McDonnell and Sikander's (2017) characterization of generalists as practitioners managing broad organizational activities, this research defines HR generalists as human resources professionals who manage and execute comprehensive HR functions throughout the employee lifecycle, including recruitment and onboarding, employee relations, benefits administration, compliance management, performance management, training and development, and organizational development. The comprehensive nature of these responsibilities makes HR generalists particularly relevant for examining AI's impact as their diverse duties include functions that are potentially subject to technological transformation. In this sense, HR generalists fulfil a dual role: on the one hand, they are subjects of AI-driven change, and on the other hand, they are change agents responsible for organizational adaptation (Charlwood & Guenole, 2022; European Commission, 2023).

Rather than focusing on technical specifications or degrees of artificial general intelligence, this study adopts a functional perspective, conceptualizing AI as digital technologies and systems capable of executing intellectual tasks traditionally performed by human intelligence in the professional context of HR (Russell & Norvig, 2022; McCarthy, 2007). This encompasses automated decision-making tools, predictive analytics, pattern recognition systems, natural language processing applications, and intelligent automation platforms that can augment, transform, or potentially replace human judgment and expertise in HR functions. This definition aligns with recent research by the European Commission (2023, pp. 11-18) that identifies three ways in which AI systems operate in HR: evaluation (monitoring and assessing employee performance), direction (assigning tasks and providing guidance), and discipline (determining performance-related consequences) (European Commission, 2023).

Traditional competency development frameworks, as presented by De Vos et al. (2011) in their integrated model, position competency development as a cyclical process centred on Personal Development Plans (PDPs), which coordinate three core pathways: training, on-the-job learning, and career management, as shown in Figure 1. These interconnected processes can improve individual employability within relatively table organizational and socio-economic environment. The temporal architecture of traditional development cycles operates on relatively fixed timescales.

The implementation and evaluation of personal development plans can unfold over a longer period of time with regular monthly or quarterly check-ins to assess progress and recalibrate the goals (Kirkpatrick & Kirkpatrick, 2006; Guskey, 2002). Training programme impact evaluation unfolds over extended periods: immediate feedback measures initial reactions, but significant behavioural changes or knowledge transfer can only be measured after 3 to 12 months (Garavaglia, 1993; Kirkpatrick & Kirkpatrick, 2006). This longer time span reflects the basic learning theory.

Kolb's (1984) experiential learning cycle requires repeated reflection, conceptualization, and active experimentation – a process that unfolds over extended periods. Knowles' (1984) Adult Learning Theory emphasizes self-directed learning and contextual engagement, both of which require significant investment of time. Similarly, Schön's (1983) theory of reflective practice views professional development as a continuous, repetitive, cyclical process of learning and adaptation rather than an immediate outcome. These learning theories agree on a fundamental principle: meaningful competency development operates on extended temporal scales, typically measured in months or years rather than weeks.

Figure 2 illustrates the AI-enhanced competency development model which was built on the model of De Vos et al. (2011), and shows how the traditional personal development plan (PDP)-centred approach – which includes training, on-the-job learning, and career management – operates in an organizational context. This framework is essential for analysing how AI disrupts traditional development cycles.

Unlike previous technological transitions that primarily affected manual or routine cognitive tasks (Frey & Osborne, 2017), AI's impact extends comprehensively across knowledge work domains, affecting professional roles traditionally isolated from automation (Brynjolfsson & McAfee, 2014). Human resource professionals occupy a particularly complex position within this transformation: they simultaneously serve as subjects of the AI-driven change – requiring adaptation of their own competency profiles – and as agents responsible for managing organizational adaptation to AI integration (Charlwood & Guenole, 2022).

AI fundamentally disrupts the temporal logic of traditional competency development. Building on the integrative model of competency development by De Vos et al. (2011), Figure 2 illustrates how the AI-Enhanced Competency Development Model disrupts traditional frameworks by introducing rapid, systemic change across multiple organizational levels.

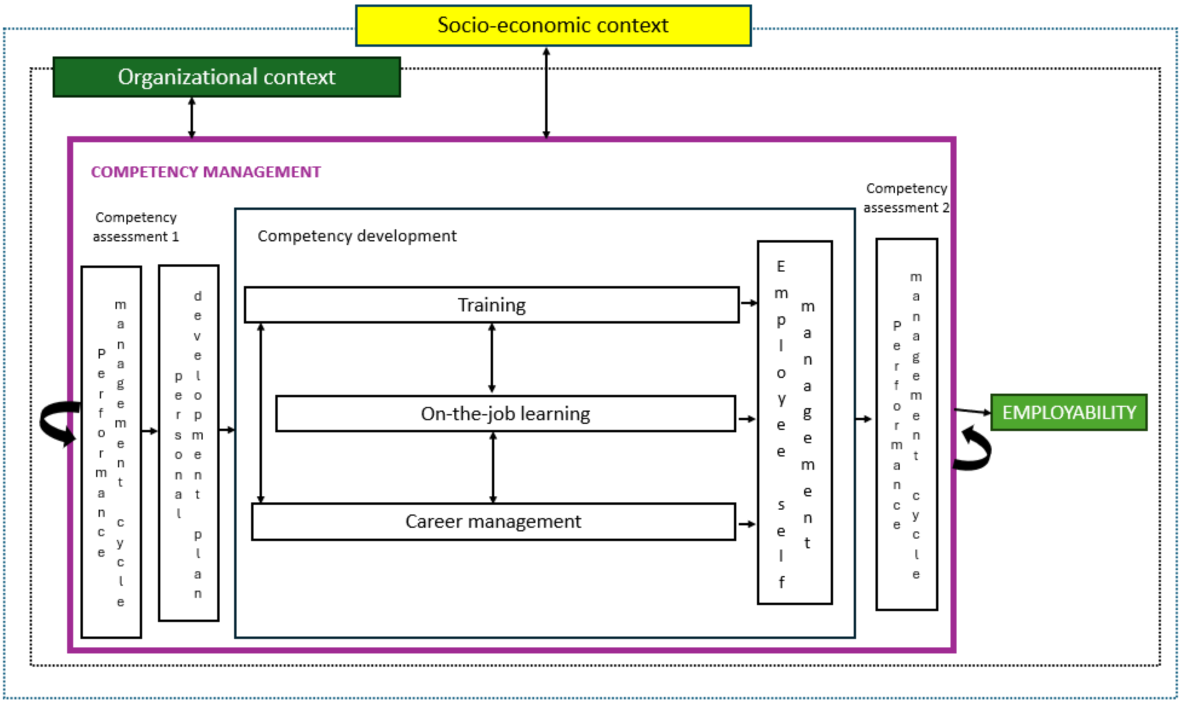

Figure 1: *Integrative model of competency development*
Source: *De Vos et al., 2011*

This AI disruption cuts across all levels of organizational functioning: the individual level as daily professional routines and learning are shaped by AI applications; the level of practitioners as HR professionals must both use and manage AI tools; and the strategic level since leaders must adapt to the broader organizational and societal impacts of AI. As shown in Figure 2, this leads to three simultaneous outcomes: accelerated obsolescence of existing competencies (Vezeteu & Năstac, 2024), constant demand for new AI-relevant skills (Babashahi et al., 2024), and a widening gap between current capabilities and market requirements undermining employability (Goulart et al., 2022).

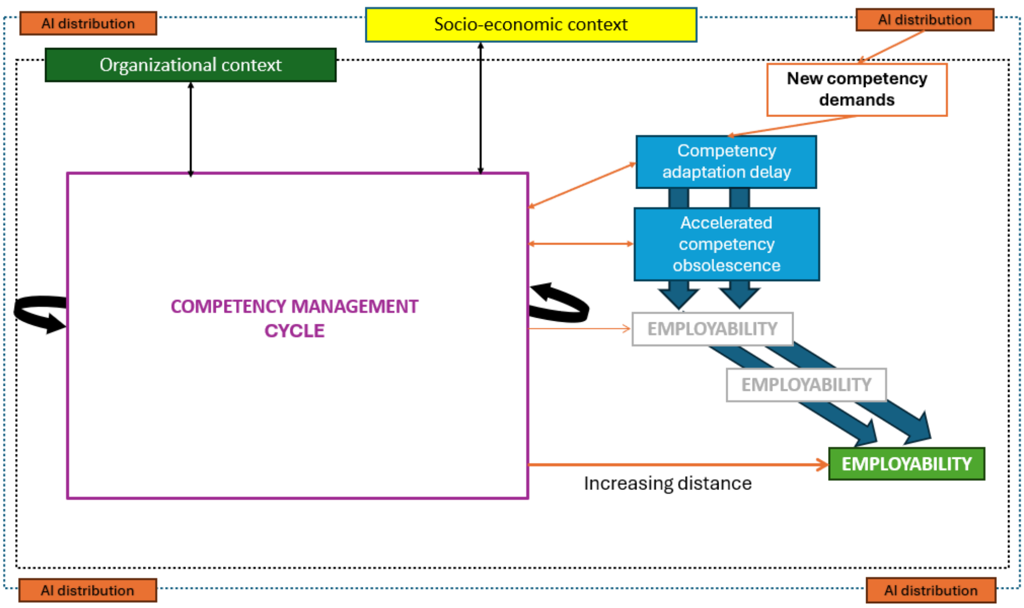

Figure 2: *The AI-Enhanced Competency Development Model is built on the model by De Vos et al. (2011)*
Source: *The author's own.*

Academic research demonstrates that skill obsolescence has intensified with technological changes. Traditional estimates of competency half-life – the period after which skills lose half their value – range from 5 to 15 years (Allen & de Grip, 2012; Deming & Noray, 2020). However, AI integration further accelerates this obsolescence timeline through two mechanisms. First, AI systems evolve at an accelerated pace. Historically, computing power doubles approximately every 18-24 months, which is a phenomenon known as Moore's Law (Buttazzo, 2023). This rapid technological advancement means that HR professionals face constantly evolving AI tools, platforms, and capabilities that require continuous skill updates. Second, organizational adoption cycles are compressing as AI tools become more accessible and integrated into HR workflows (European Commission, 2023). This creates a fundamental structural mismatch: while traditional professional development operates on annual or multi-year cycles (training programmes, career progression, and certification renewal), AI-driven competency requirements change on a quarterly or even monthly basis as new systems are introduced and existing systems are updated.

While extensive research examines AI's impact on various occupational domains (Frey & Osborne, 2017; Brynjolfsson & McAfee, 2014) and specific HRM functions such as recruitment (Albassam, 2023; Black & Van Esch, 2020) and talent management (Jacob et al., 2023), the latest research provides critical evidence on AI's transformative power on professional competencies. Arshad et al. (2025) demonstrate that AI serves as an augmentation tool rather than a replacement mechanism, and reshapes skill composition towards non-routine cognitive and interpersonal domains. Amayreh et al. (2025) provide evidence that AI experience, use, technical ability, and perceived usefulness have a significant positive effect on employee self-competence. Piwowar-Sulej et al. (2024) examine AI's influence on future competencies, while Raman et al. (2024) evaluate AI's performance in HR queries, highlighting its complementary role. Aguinis et al. (2024) emphasize the diverse competencies needed to manage HR roles with AI assistance.

These studies collectively demonstrate that AI integration imposes dual competency requirements: on the one hand, there is a demand for new technical capabilities, while on the other hand, the importance of interpersonal, ethical, and strategic competencies persists and even grows. Evidence suggests that organizations cannot achieve adaptation through technical upskilling alone; instead, they require comprehensive competency transformation spanning technical, interpersonal, and strategic domains.

Effective competency development depends on the organizational context, and not merely on individual effort. As documented in basic learning theories, competency development requires structured organizational support. Kolb's experiential learning cycle requires structured reflection and practice opportunities; Knowles' adult learning theory emphasizes self-directed learning in supportive contexts; and Schön's reflective practice states that professional development requires organizational conditions enabling continuous experimentation and feedback (Tracey et al., 1995).

The structural timing gap identified through the analysis of traditional development mechanisms (annual or multi-year operating cycles) versus AI-driven requirements (quarterly or monthly schedules) suggests that individual HR professionals – regardless of age or familiarity with digital technologies – are struggling to overcome systemic organizational barriers to rapid learning, such as inadequate training infrastructure, misalignment between AI deployment and the timing of training, and organizational culture barriers that discourage risk-taking and experimentation. This creates a multi-level adaptation challenge where organizations must align learning infrastructure, training programs, and psychological safety mechanisms with the accelerated pace of AI-driven transformation (Ranasinghe et al., 2024; European Commission, 2023, pp. 87-98).

Through the literature reviewed above it is possible to establish several converging insights:

1. Transformation of competencies is fundamentally temporal. Traditional development mechanisms operate on relatively fixed, extended timescales (3-12 months for training evaluation, annual or multi-year career progression), and reflect underlying learning theory principles.
2. AI disruption accelerates obsolescence across skills, jobs and organizational models. Evolution of computing power (Moore's Law) and reduced adoption cycles on organizational level create rapidly changing competency requirements with a shift to quarterly or monthly timescales.
3. There isa structural timing mismatch. The divergence between slow organizational learning cycles and rapid technological change creates conditions where continuous professional development efforts may prove insufficient to maintain employability.
4. The impact is multi-level. The disruption caused by AI affects individual competency development, organizational workforce planning and training infrastructure as well as systemic educational and professional standards.
5. The organizational context is crucial. Individual adaptability primarily depends on organizational enablers – such as learning infrastructure, psychological safety, and the coordination and scheduling of training programs – rather than on individual characteristics alone.

The literature review is organized around five interlinked building blocks that jointly underpin the competency speed gap framework. First, competency theory frames competencies as dynamic, context-dependent capabilities. Second, the role of HR generalists is specified, and their broad functional remit and dual position as both subjects of AI-driven change and agents of organizational adaptation are emphasized. Third, a functional definition of AI in HR is outlined focusing on how AI systems support evaluation, direction and discipline in HR processes. Fourth, traditional competency development and learning theories show that competency growth unfolds through PDP-based, multi-pathway processes on extended temporal scales. Finally, AI's impact on these temporal dynamics is analysed, which reveals a structural misalignment between rapidly accelerating AI-driven competency obsolescence and the slower pace of organizational learning. Building on these insights, the following section introduces the competency speed gap framework as a conceptual model that formalizes these temporal dynamics and positions them both as a critical research challenge and as a phenomenon that can be addressed at the organizational level.

Conceptual Framework

As we have seen, in contrast to AI-induced acceleration of competency obsolescence, traditional organizational learning cycles have relatively fixed timescales. This section attempts to establish a framework for the emerging competency speed gap, which is crucial for the formal representation of the temporal dynamics of competency transformation. In doing so, the author will seek to identify the mechanisms through which AI integration creates an increasing gap between the rate of competency obsolescence and organizational learning capacity.

The competency speed gap framework captures the widening temporal disconnect between two competing speeds: the accelerating rate of competency obsolescence driven by AI-powered innovation and the relatively fixed pace of organizational learning and development cycles. This framework extends beyond existing constructs of skill obsolescence (Frey & Osborne, 2017) and skills gaps (Novak et al., 2015; Ravi & Sumathi, 2023; Sartori et al., 2022) by specifically addressing the temporal dimension of competency disruption. The competency speed gap creates a structural condition where even continuous professional development efforts may prove insufficient to maintain employability, as target competency requirements shift faster than development mechanisms could respond.

Competency speed gap is distinguished by three main characteristics:

Exponential divergence: the gap widens over time as AI capabilities advance faster than human adaptation mechanisms (Buttazzo, 2023).

Structural asymmetry: traditional development pathways (training cycles, career progression, experiential learning) operate at fundamentally different temporal scales than AI-driven change (Bühler et al., 2022; Chuang et al., 2024).

Multi-level impact: the gap manifests simultaneously at individual (personal capability development), organizational (workforce planning and training), and systemic (educational curricula and professional standards) levels (Bankins et al., 2024).

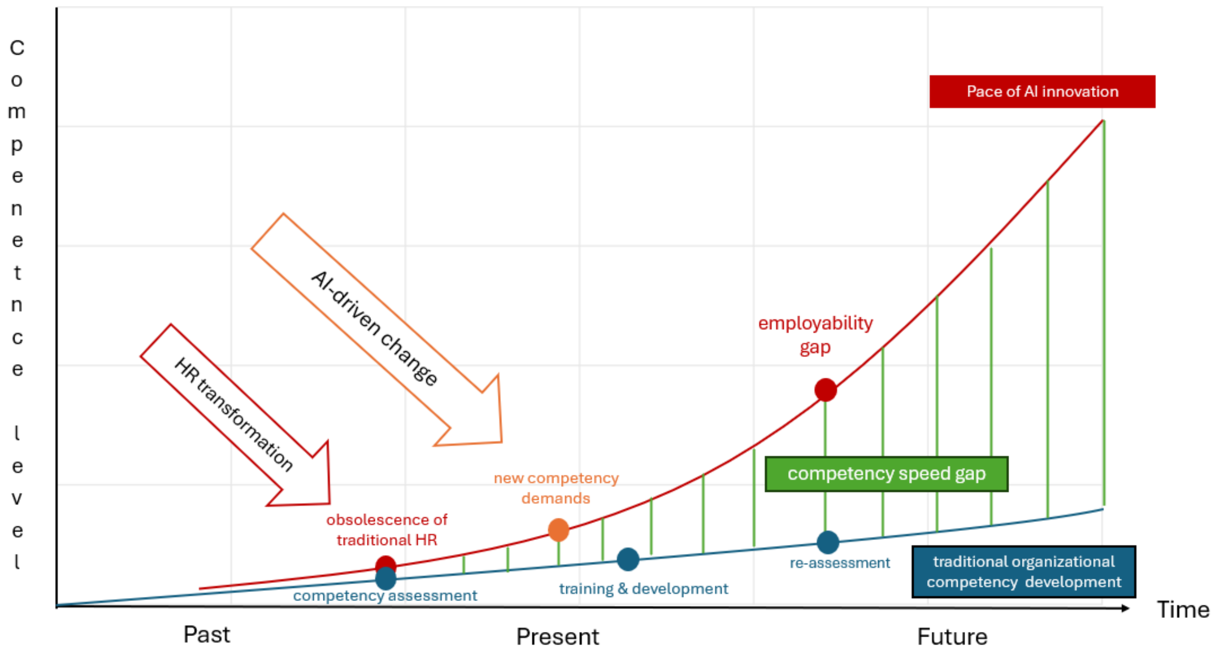

Figure 3: *The core mechanism of the competency speed gap.*
Source: *The author's own.*

Figure 3 illustrates the basic mechanism of the competency speed gap, and shows how the pace of AI-powered innovation (indicated by the rising red line) diverges exponentially from the pace of traditional organizational competency development (indicated by the rising blue line). This exponential divergence creates an expanding employability gap over time, where the distance between current capabilities and market requirements continuously widens despite the ongoing professional development efforts.

Four Theoretical Predictions: Mechanisms of Competency Transformation

This temporal divergence manifests through four distinct but interconnected mechanisms. The following predictions specify how AI integration will reshape competency requirements at different levels of analysis from the structure of work itself to the organizational and individual conditions that shape the adaptation process.

P1: Competency Polarization: Based on the literature review's discussion on the multi-level disruptive effect of AI, which shows that AI-powered innovation creates a demand for new technical skills while maintaining the strategic importance of relational skills, this research predicts that AI integration will polarize competency requirements between demands for new technical abilities and improved interpersonal skills.

In practice, this means that HR professionals will be faced with a simultaneous demand for new technical skills, such as prompt engineering, data interpretation, and the use of AI-powered collaboration tools (Babashahi et al., 2024; Korzynski et al., 2023) while relational and social-emotional skills will gain more strategic importance in contexts requiring trust, ethical judgment, and complex interpersonal navigation (Bobitan et al., 2024). As noted in the literature review, AI systems can execute evaluation, direction, and discipline functions, yet employees often prefer human engagement for decisions involving emotional support, trust, or vulnerability (Rubin et al., 2025). This creates a polarized competency landscape in which both technical and relational capabilities are essential yet develop at different paces.

P2: Task-Level Transformation: Drawing on the framework of the competency speed gap presented in Figure 3, which shows exponential divergence between technology and learning cycles, this study predicts that AI will transform HR work at the task level rather than at the job level, and will automate certain (routine and repetitive) task elements while creating space for higher-value activities requiring creativity, critical thinking, strategic planning, and human judgment. The literature review established that traditional competency development operates as a multi-pathway process where training, on-the-job learning, and career management operate in concert. However, disruptions caused by AI show that routine, administrative tasks, such as screening job applications, scheduling interviews, or processing routine compliance checks have become prime candidates for automation while opportunities for higher-value activities like strategic consulting, complex problem-solving and change management continue to expand (Sundari et al., 2024). Rather than eliminating HR roles, this task-level transformation encourages the evolution of different roles, with competency requirements shifting from administrative and routine analytical tasks towards strategic, interpersonal, and complex cognitive domains (Nishar, 2023).

P3: Hybrid Collaboration Models: Building on the analysis of organizational learning cycles presented in the literature review, which reveal a slower pace for traditional development mechanisms (3-12 months for training evaluation), this research predicts that optimal HR performance will emerge from the collaboration of human with AI rather than humans' substitution by artificial intelligence. This is so as empirical evidence demonstrates that the highest productivity gains can be reached when humans and AI operate in complementary roles. The temporal dynamics outlined in the competency speed gap framework shows that organizations are currently facing a structural timing gap where the development of human skills unfolds in annual or multi-year windows while AI-driven requirements shift quarterly or monthly. This mismatch creates a necessity for a paradigm shift away from automation-focused models (where AI replaces human judgment) towards partnership-focused models (where humans and AI work together to enhance their complementary strengths). Evidence from studies on human-AI teams demonstrates that complementarity – where humans represent judgment, context interpretation, and ethical decision-making while AI handles data processing and pattern recognition – tended to outperform humans or AI working independently (Przegalińska et al., 2025; Vaccaro et al., 2024). This hybrid collaboration paradigm requires new competencies in managing hybrid workflows, validating AI outputs, and allocating tasks appropriately between humans and machines (Sidra & Mason, 2025; Hemmer et al., 2025).

P4: Organizational Enabler Primacy: Based on the multi-level analysis of competency transformation presented in Figure 2, which demonstrates that AI-induced disruption extends to multiple levels including the individual, HR professionals, and the strategic level, this research predicts that successful adaptation to the accelerating competency requirements depends more on organizational enablers than on individual characteristics such as age or previous technical experience. As documented in the literature review, learning theory emphasizes that competency development depends not merely on individual effort but on organizational context: Kolb's experiential learning cycle requires structured reflection and practice; Knowles' adult learning theory emphasizes self-directed learning in supportive contexts; and according to Schön's reflective practice, professional development requires organizational conditions enabling continuous experimentation and feedback. The structural timing gap identified in the competency speed gap framework, as presented in Figure 3, suggests that individual HR professionals, regardless of age or technical familiarity, cannot overcome systemic organizational barriers to rapid learning such as inadequate training infrastructure, misalignment between AI deployment and the scheduling of training programmes, or organizational cultures that discourage risk-taking and experimentation. Therefore, while individual HR professionals cannot overcome these obstacles on their own, adaptability is managed at the organizational level through institutional redesign of learning systems, training infrastructure, and psychological safety, thus turning the competency speed gap into a manageable organizational challenge rather than an inevitable individual shortcoming (Tracey et al., 1995; Ranasinghe et al., 2024; European Commission, 2023, pp. 87-98).

Propositions for future research

The competency speed gap framework and the above described four predictions (P1-P4) require empirical validation through quantitative research. To advance from conceptual foundation to measurable construct, future research should test the following propositions.

T1: HR professionals working in AI-integrated environments will report significantly higher demand for both technical competencies (e.g., data interpretation, AI tool proficiency, prompt engineering) and interpersonal competencies (e.g., emotional intelligence, ethical judgment, trust-building) compared to HR professionals in environments without AI integration.

T2: Organizations with rapid AI deployment will exhibit greater competency speed gaps than organizations where AI integration is carried out gradually. This proposition examines whether faster technological change creates greater differences in learning systems regardless of the industry or organizational size.

T3: The competency speed gap will be greater when organizations deploy AI systems before establishing training infrastructures, compared to instances when training programs are implemented simultaneously with or prior to the introduction of AI. This proposition examines how the sequencing of AI adoption and the preparation of learning systems affects the pace of competency adjustment.

T4: HR professionals in organizations with a culture of continuous learning will adapt faster to AI-driven competency changes than those in organizations that use traditional training approaches. This difference is unrelated to individual factors such as age or previous technical experience. This proposition highlights that organizational context has a more powerful impact than personal characteristics.

T5: Organizations that emphasize human-AI partnership models will achieve better outcomes (employee satisfaction, role clarity, performance) than organizations focused on AI-driven automation or task substitution. This assumption explores whether collaboration frameworks moderate the relationship between AI integration and the transformation of HR roles.

T6: The rate of competency obsolescence – the speed at which skills lose their practical value – will increase as AI system updates become more frequent and the adoption of technology accelerates. This proposition captures the core temporal mechanism of the speed gap.

Table 1 shows how theoretical predictions align with operationalized propositions and highlight how organizational enablers, temporal dynamics, and competency transformation mechanisms can be measured and tested in HR practice and research.

Table 1: *Theoretical Predictions and Testable propositions in the competency speed gap framework*

Prediction	**Core claim**	**Testable proposition**
P1: Competency Polarization	AI creates a simultaneous demand for technical and interpersonal skills.	T1
P2: Task-Level Transformation	AI transforms tasks (not entire jobs); automates routine work while expanding higher-value activities.	T5
P3: Hybrid Collaboration Models	Human-AI partnership outperforms substitution; complementarity between human judgment and AI data processing.	T5
P4: Organizational Enabler Primacy	Organizational factors are stronger predictors than individual characteristics (age, prior technical experience).	T2, T3, T4
Core Mechanism: Temporal Dynamics of the Speed Gap	The speed gap widens as AI accelerates; the obsolescence rate increases and skill half-life decreases.	T6

These claims can be verified through cross-sectional surveys comparing organizations using different AI adoption strategies, longitudinal studies tracking changes in competencies over time, or experimental plans testing specific training interventions. Quantitative validation would establish the competency speed gap as a measurable framework for organizational practice and the development of specific HR policies.

Conclusion

This paper has introduced the competency speed gap as a conceptual framework for understanding the temporal dynamics of competency transformation in AI-integrated HR environments. By synthesizing existing literature on competency development, AI integration, and organizational learning, the framework captures the widening difference between the accelerating pace of AI-driven competency obsolescence and the relatively fixed speed of traditional professional development mechanisms. The four theoretical predictions (P1–P4) and six testable propositions (T1–T6) presented above provide a foundation for future quantitative research examining the conditions under which the competency speed gap emerges, widens, or becomes manageable at the organizational level.

The competency speed gap framework makes three contributions to existing theory. First, it introduces a temporal dimension to the competency literature positioning the challenge not as a static skills gap but as a dynamic speed differential. Second, it extends the AI-in-HRM literature by conceptualizing HR generalists as occupying a dual position – simultaneously subjects of AI-driven change and agents responsible for organizational adaptation. Third, the framework synthesizes learning theory (Kolb, Knowles, Schön) with technology adoption research, and highlights the structural asymmetry between human learning cycles and AI-driven requirement changes.

For HR practitioners and organizational leaders, the competency speed gap framework suggests several actionable priorities. Organizations should align AI deployment timelines with training infrastructure development, and ought to ensure that learning systems are established before or simultaneously with technology introduction (as proposed in T3). Investment in continuous learning cultures – rather than episodic training interventions – appears critical for managing accelerating competency requirements (T4). Additionally, prioritizing human-AI partnership models over substitution-focused automation may yield superior outcomes in employee satisfaction, role clarity, and performance (T5). For HR education institutions, the framework implies a need to reconsider curriculum design, incorporating both technical AI literacy and interpersonal competencies that remain strategically important in AI-integrated environments.

This study has several limitations that must be acknowledged. As a conceptual paper, the competency speed gap framework and its propositions require empirical validation through quantitative research. The framework was developed primarily through literature synthesis rather than primary data collection, which limits the specificity of the claims. Additionally, the analysis focuses on HR generalists in organizational contexts, and the applicability of the framework to other professional domains or to HR specialists remains to be examined. Finally, the propositions assume relatively stable organizational environments; the framework may require adaptation for organizations undergoing simultaneous transformations (e.g., mergers, restructuring) beyond AI integration. Several research directions emerge from this framework. First, longitudinal studies tracking competency evolution in organizations with different AI adoption strategies would provide direct tests of propositions T2, T3, and T6. Second, comparative research across industries with varying AI penetration rates could illuminate contextual moderators of the competency speed gap. Third, scale development research is needed to operationalize the competency speed gap as a measurable construct potentially incorporating both objective measures (skill currency, training lag) and subjective assessments (perceived obsolescence, learning anxiety). Fourth, intervention studies testing specific organizational strategies – such as accelerated learning cycles, AI-literacy programs, or hybrid collaboration training – would establish evidence-based practices for managing the speed gap. In conclusion, the competency speed gap represents not an inevitable individual shortcoming but an organizational challenge that can be addressed through institutional transformation. Organizations that recognize this temporal dynamic and invest in aligned learning infrastructure, continuous development cultures, and human-AI collaboration models will be better positioned to turn AI integration from a disruptive threat into a catalyst for strategic competency development.

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