

A Narrative Process Theory of AI Integration into Talent Acquisition

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Abstract:

Research Question: How can AI integration into Talent Acquisition be conceptualized as a recursive organizational process through which AI-enabled organizational capabilities emerge over time? **Motivation:** Research on AI in Human Resource Management has generated important insights into technology adoption, digital HRM, and algorithmic decision-making. However, it has largely conceptualized AI integration as a technology implementation challenge, providing limited explanation of how AI-enabled organizational capabilities emerge through organizational processes. Motivated by practical challenges associated with AI integration in Talent Acquisition, this paper develops a narrative process theory that conceptualizes AI integration as a recursive organizational process rather than a linear implementation sequence. Building on process theory, the proposed framework shifts attention from technology adoption to capability emergence, providing a richer explanation of AI-enabled organizational transformation. **Idea:** The paper develops a narrative process theory in which AI integration unfolds through three recursive phases—Initiation, Diffusion, and Routinization—linked by collective sensemaking, experimentation and enactment, and reflexive learning and institutionalization. These generative mechanisms explain how AI-enabled Talent Acquisition capability progressively emerges through organizational action. **Data:** This is a conceptual study. The analysis synthesizes and integrates literature on AI in Human Resource Management, process theory, organizational routines, and dynamic capabilities to develop a theoretically grounded process framework. **Findings:** AI-enabled Talent Acquisition capability emerges through three interconnected phases linked by generative mechanisms connecting organizational interpretation, experimentation, and learning. The recursive process explains how AI-supported practices emerge, stabilize, and evolve through organizational action. The framework extends AI in HRM research by explaining capability emergence through organizational processes and provides a foundation for future empirical research. **Contribution:** The paper introduces a narrative process theory explaining AI integration through recursive organizational capability development, extending AI in HRM, process theory, and organizational capability research.

Keywords: artificial intelligence, talent acquisition, process theory, organizational capability, human resource management

JEL Classification: M12, M15, O33

1. Introduction

Artificial intelligence (AI) is rapidly transforming Talent Acquisition by reshaping how organizations identify, evaluate, and recruit talent. AI-enabled applications support candidate sourcing, résumé screening, applicant matching, predictive assessment, and talent analytics, improving recruitment efficiency, decision quality, and organizational responsiveness in increasingly competitive labour markets. AI has therefore become an important component of contemporary Human Resource Management (HRM).

The growing adoption of AI has attracted substantial scholarly attention. Existing research has examined technology adoption, implementation success, algorithmic decision-making, ethical governance, and digital HRM, providing valuable insights into the opportunities and challenges associated with AI-enabled HRM.

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More recently, scholars have emphasized that AI transforms not only recruitment technologies but also the nature of work, professional roles, and organizational coordination, requiring greater attention to human–AI collaboration and evolving work practices (Faraj et al., 2018; Kellogg et al., 2020; Jarrahi, 2018).

However, most research continues to conceptualize AI integration primarily as a technology adoption or implementation phenomenon. Consequently, attention has focused on implementation antecedents, facilitators, and outcomes rather than on how organizations progressively develop AI-enabled capabilities through everyday organizational activity. Yet organizations introducing similar technologies often follow markedly different trajectories: some embed AI into routine Talent Acquisition practices, whereas others remain confined to fragmented pilots or isolated applications. Explaining this variation requires understanding AI integration as an organizational process unfolding over time.

Talent Acquisition illustrates this challenge particularly well because AI integration involves multiple actors, evolving professional roles, governance arrangements, and organizational routines. Rather than a discrete implementation event, AI integration unfolds as an ongoing organizational process through which actors interpret technological opportunities, experiment with new work practices, and progressively embed successful practices into organizational routines. This shift reflects a broader movement in organization studies from viewing AI as a technological artefact toward understanding AI as a phenomenon that reshapes organizing, work practices, and capability development (Faraj et al., 2018; Kellogg et al., 2020; Orlikowski, 2000).

Responding to this theoretical gap, this paper develops a narrative process theory explaining how AI-enabled Talent Acquisition capability emerges through recursive organizational interaction. Drawing on process theory and contemporary process thinking, AI integration is conceptualized as three interrelated phases—Initiation, Diffusion, and Routinization—connected by three mutually reinforcing generative mechanisms: collective sensemaking, experimentation and enactment, and reflexive learning and institutionalization. The framework shifts attention from technology adoption to capability emergence by explaining how actors progressively construct AI-enabled capability through interaction, learning, and routine development.

2. Theoretical Background

2.1 AI in talent acquisition: from technology adoption to organizational transformation

Artificial intelligence has become one of the most influential technological developments shaping contemporary Human Resource Management (HRM), particularly Talent Acquisition. AI-enabled applications support candidate sourcing, résumé screening, job matching, predictive assessment, and talent analytics, improving recruitment efficiency while managing growing volumes of applicant data. Recent organizational research further suggests that AI extends beyond automation by reshaping professional judgment, coordination mechanisms, and collaboration between humans and intelligent systems (Faraj et al., 2018; Kellogg et al., 2020).

The growing adoption of AI has stimulated extensive research in HRM and Talent Acquisition. Existing studies have examined technology adoption, implementation success, algorithmic decision-making, fairness, transparency, and digital HRM (Parry & Strohmeier, 2014; Strohmeier, 2020). More recent research has addressed ethical challenges, explainability, algorithmic bias, and responsible AI governance, emphasizing that successful implementation depends not only on technological sophistication but also on organizational trust, transparency, and human oversight.

Despite these contributions, the dominant literature continues to conceptualize AI integration primarily as a technology adoption or implementation phenomenon. Research has focused on antecedents, facilitators, barriers, and implementation outcomes, explaining success through technology acceptance, implementation quality, or organizational readiness. Although these perspectives have advanced understanding of AI adoption in HRM, they provide limited insight into how organizations progressively develop AI-enabled capabilities through interaction during implementation.

AI integration nevertheless differs from the integration of earlier digital technologies in several theoretically important ways. Unlike conventional information systems that primarily automate, standardize, or support predefined tasks, learning algorithms can generate classifications, predictions, and recommendations in domains that have traditionally relied on human expertise and judgment (Faraj et al., 2018). Their integra-

tion may therefore reshape expertise, occupational boundaries, coordination, and control rather than merely alter the technological infrastructure through which work is performed (Faraj et al., 2018; Kellogg et al., 2020). In organizational decision making, this creates a shifting division of work between humans and AI, requiring organizations to determine how analytical capabilities of AI should be combined with human judgment under conditions of uncertainty and equivocality (Jarrahi, 2018).

AI integration is also distinctive because AI-generated outputs may be probabilistic, difficult to explain, and sensitive to the data and contexts in which systems operate. Organizational actors must therefore learn not only how to use a technology but also when to rely on, question, override, or complement its recommendations. In Talent Acquisition, where AI-supported decisions can directly affect employment opportunities, these characteristics introduce additional concerns regarding fairness, transparency, accountability, and legitimacy. Integration consequently requires continuing evaluation of both technological performance and the evolving relationship between algorithmic recommendations and human professional judgment.

These characteristics make AI integration an inherently recursive organizational phenomenon. As actors interact with AI systems, they develop new interpretations of their capabilities and limitations, modify work practices, redefine human and technological roles, and revise governance arrangements in response to experience. AI integration therefore cannot be reduced to the implementation and subsequent use of a technological artefact. It involves the ongoing construction and reconstruction of human–AI work practices through which organizational capability progressively emerges. Unlike the integration of earlier recruitment technologies, where routinization primarily concerned workflow standardization and user adoption, AI integration requires continuous recalibration of the relationship between algorithmic outputs and human professional judgment across all three phases.

Accordingly, this paper argues that AI integration should be understood not merely as technological implementation but as an organizational transformation process. Rather than asking why organizations adopt AI, the more fundamental question is how AI-enabled Talent Acquisition capabilities emerge through organizational action, interaction, experimentation, and learning. Addressing this question requires a process perspective capable of explaining dynamic organizational change rather than static relationships among implementation variables.

2.2 Why a process perspective?

Research on AI integration in Talent Acquisition has predominantly adopted variance-oriented perspectives explaining the antecedents, determinants, and outcomes of successful implementation. These approaches have advanced understanding of AI adoption, user acceptance, organizational readiness, ethical concerns, and implementation effectiveness. However, by focusing on relationships among variables, they provide limited insight into how AI integration unfolds as an organizational process.

This limitation is particularly relevant in Talent Acquisition, where AI integration extends beyond implementing digital technologies. Recruitment involves continuous interaction among organizational actors, professional roles, governance arrangements, and organizational routines. Organizational transformation is therefore better understood as a process through which actors interpret technological opportunities, experiment with work practices, adapt routines, and progressively develop organizational capabilities rather than as a single implementation decision.

Process theory provides an appropriate theoretical lens because it shifts attention from relationships among variables to events, activities, interactions, and trajectories unfolding over time (Van de Ven & Poole, 1995; Langley, 1999). Rather than explaining why outcomes differ, process perspectives explain how phenomena emerge, evolve, stabilize, and transform. This emphasis on temporality and generative mechanisms makes process theory particularly suitable for explaining AI integration, where capability develops progressively rather than immediately following implementation.

Recent developments in process scholarship further emphasize that organizational phenomena are explained through events, actors, activities, and generative mechanisms rather than predefined causal relationships among variables. Cloutier and Langley (2020) argue that process-theoretical contributions should present coherent narratives explaining how phenomena unfold over time while accounting for recursive interactions, multiple developmental pathways, and evolving organizational contexts. This perspective is particularly valuable for conceptual research examining dynamic organizational processes rather than predicting outcomes.

A process perspective also shifts attention from technology-centred to organization-centred explanations of AI integration. Rather than treating AI as the primary driver of organizational transformation, process theory suggests that technologies acquire organizational significance through actors who interpret technological possibilities, negotiate work practices, experiment with alternative arrangements, and adapt them through experience. Organizational capability therefore emerges not from technology itself but from recursive interaction among actors, learning processes, and organizational routines. This argument is consistent with practice-based perspectives suggesting that technologies acquire organizational meaning through situated use rather than through their technical properties alone (Orlikowski, 2000).

EXISTING PERSPECTIVES	PROPOSED THEORY
 AI adoption	 Capability emergence
 Technology implementation	 Organizational process
 Linear implementation stages	 Recursive organizational phases
 Technology acceptance	 Collective sensemaking
 Implementation success	 Experimentation & enactment
 Stable implementation outcomes	 Reflexive learning & institutionalization
 Technology as the driver	 Organizational actors as the drivers
 End of implementation	 Continuous capability renewal

Figure 1: Existing Perspectives vs. Proposed Theory

Building on these foundations, AI integration into Talent Acquisition is conceptualized as a recursive organizational process comprising three interrelated phases—Initiation, Diffusion, and Routinization — linked by three generative mechanisms: collective sensemaking, experimentation and enactment, and reflexive learning and institutionalization. Together, these mechanisms explain how AI-enabled Talent Acquisition capability emerges, extending AI in HRM research and contemporary process theory (Figure 1).

3. A Narrative Process Theory of AI Integration into Talent Acquisition

Organizations rarely initiate AI integration simply because new technologies become available. Instead, AI initiatives emerge when existing Talent Acquisition practices no longer respond effectively to changing labour market conditions, increasing recruitment complexity, or rising expectations regarding speed, quality, and candidate experience. This observation is consistent with research suggesting that organizational change is triggered by discrepancies between existing practices and evolving environmental demands rather than by technology itself (Van de Ven & Poole, 1995; Vial, 2019).

AI integration is conceptualized as a recursive organizational process through which Talent Acquisition capability emerges. Rather than resulting directly from technology implementation, capability develops as actors interpret technological possibilities, experiment with work practices, reflect on experience, and institutionalize practices that create organizational value. This understanding builds on process perspectives viewing organizational change as evolving through action, interpretation, and adaptation rather than linear implementation stages (Langley, 1999; Pentland, 1999).



Figure 2: Process Phases of AI Integration into Talent Acquisition

The proposed theory explains AI integration through three interrelated phases linked by three mutually reinforcing generative mechanisms: collective sensemaking, experimentation and enactment, and reflexive learning and institutionalization. Importantly, the role of AI differs across these phases. During Initiation, actors interpret AI opportunities, risks, and appropriate boundaries for human-AI decision making; during Diffusion, they experiment with and negotiate AI-supported work practices; and during Routinization, they embed, govern, monitor, and continuously recalibrate these practices. Together, these mechanisms explain how AI-enabled Talent Acquisition capability emerges, stabilizes, and evolves. The recursive relationships among these phases and mechanisms are illustrated in Figure 2, providing a process explanation of the generative dynamics underlying AI-enabled Talent Acquisition capability (Pentland, 1999; Langley, 1999; Langley et al., 2013).

3.1 Initiation: making sense of AI integration

The initiation of AI integration into Talent Acquisition begins long before an AI application is selected or implemented. Rather than representing a technology-driven event, it starts when existing routines can no longer respond to evolving environmental demands, prompting organizations to reconsider established ways of working (Van de Ven & Poole, 1995; Langley, 1999). AI integration therefore begins when existing recruitment practices become insufficient under changing organizational and labour market conditions. Intensifying competition for talent, rising expectations regarding recruitment speed and candidate experience, growing applicant volumes, and pressure to improve decision quality expose the limitations of established Talent Acquisition practices. Rather than creating an immediate demand for AI, these pressures encourage organizations to rethink how recruitment is organized and coordinated.

At this stage, the challenge is interpretive rather than technological. Before evaluating AI solutions, organizational actors develop a shared understanding of the problems requiring attention and determine whether AI can meaningfully address them. This assessment extends beyond identifying potential efficiency gains. Because AI may participate in prediction, evaluation, and recommendation, organizations must also consider its limitations and risks and determine where AI should augment human expertise, where human judgment should remain decisive, and how decision authority and accountability should be distributed (Jarrahi, 2018). In Talent Acquisition, these considerations are particularly important because AI-supported practices may affect candidate opportunities and raise concerns related to fairness, transparency, privacy, explainability, and accountability (Reddy Yanamala, 2023). This reflects the sensemaking perspective, which argues that organizational action is preceded by processes through which actors interpret ambiguity, negotiate meaning, and construct shared understandings enabling coordinated action (Weick, 1995; Maitlis & Christianson, 2014). Accordingly, the initiation phase is characterized by collective interpretation rather than technological decision-making. Senior managers, Talent Acquisition leaders, recruiters, HR professionals,

and technology specialists frequently hold different assumptions about the benefits, risks, and organizational consequences of AI integration, reflecting their professional roles and prior experience.

Collective sensemaking gradually reduces these differences through discussion, negotiation, and repeated interaction. Actors develop a shared understanding of why change is necessary, which recruitment activities may benefit from AI support, which risks and limitations require attention, and where appropriate boundaries between AI-supported decision making and human professional judgment should be established. Consensus is rarely complete; instead, sufficient alignment enables coordinated experimentation while preserving opportunities for learning and adaptation. This movement from multiple interpretations to coordinated action is consistent with process perspectives explaining organizational change as an evolving sequence of interdependent actions rather than discrete implementation decisions (Langley, 1999; Pentland, 1999).

The primary outcome of the initiation phase is not AI adoption but the creation of an organizational foundation for experimentation. Once a shared understanding of the organizational challenge, AI's potential role, and appropriate human–AI boundaries is established, organizations can move from interpretation to coordinated action. As illustrated in Figure 3, collective sensemaking connects the recognition of capability gaps with the interpretation of AI opportunities and risks, the definition of human–AI boundaries, and the development of shared organizational understanding. It therefore serves as a generative mechanism enabling the transition from uncertainty to coordinated AI experimentation (Pentland, 1999).

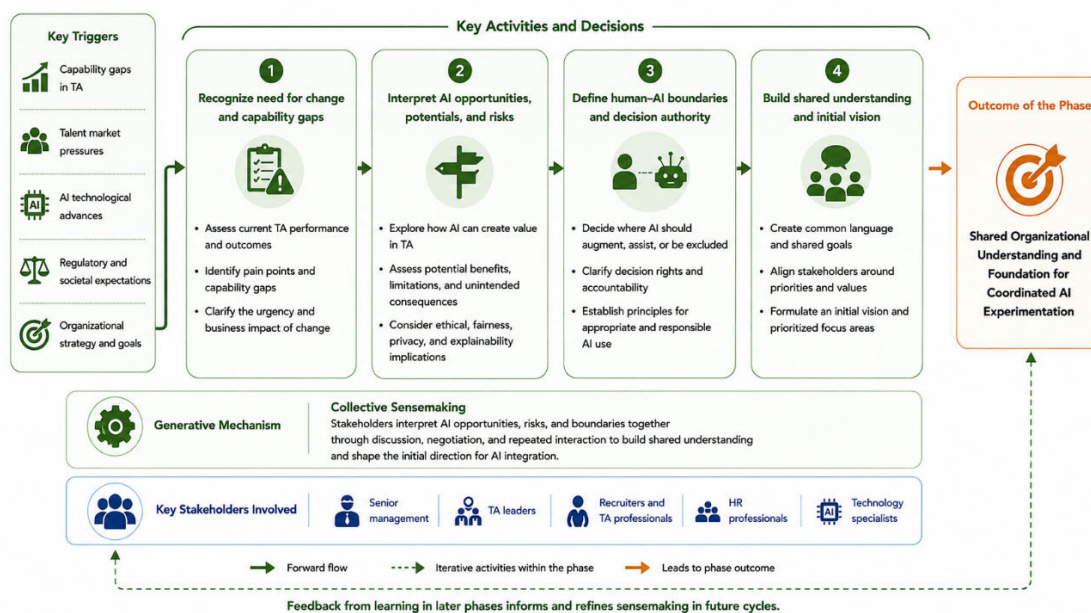


Figure 3: Initiation Phase of AI Integration into Talent Acquisition

3.2 Diffusion: experimenting, negotiating and coordinating new practices

Once organizational actors establish a shared understanding of AI integration, attention shifts from interpretation to action. The diffusion phase is characterized by experimentation in which AI-supported recruitment practices are explored, modified, evaluated, and coordinated across organizational units. Rather than implementing technological solutions, diffusion involves continuous interaction between technological possibilities and organizational routines, through which new practices emerge by enactment, variation, and adaptation rather than linear implementation (Pentland, 1999; Langley, 1999).

Experimentation is inherently distributed. Recruiters, Talent Acquisition leaders, HR professionals, and technology specialists engage with AI according to their professional roles, generating multiple trajectories of AI integration. This reflects the performative nature of organizational routines, which are continuously recreated through situated action rather than predefined procedures (Feldman & Pentland, 2003). As AI becomes embedded within everyday work, experimentation reshapes professional judgment, coordination, and organizational routines. Unlike experimentation with technologies that primarily automate predefined tasks, experimentation with AI also requires organizational actors to learn when to rely on, question, override, or complement algorithmic outputs with human judgment. Diffusion therefore involves not only adapting work-

flows to technology but also progressively calibrating the relationship between AI-generated recommendations and human professional discretion (Faraj et al., 2018; Jarrahi, 2018; Kellogg et al., 2020).

AI-supported practices are continuously evaluated in terms of accuracy, fairness, transparency, accountability, legitimacy, and alignment with organizational values and recruitment objectives. Feedback from these experiments enables organizational actors to reassess both the performance of AI systems and the appropriateness of emerging human–AI work arrangements. This iterative evaluation resembles the ongoing sensemaking process described by Maitlis and Christianson (2014), in which new experiences reshape subsequent interpretations and actions. Experimentation may therefore lead not only to the refinement of AI-supported practices but also to the reconsideration of assumptions and boundaries established during the Initiation phase.

Diffusion is neither linear nor inevitable. Developmental pathways vary according to leadership commitment, digital capabilities, organizational trust, governance arrangements, and previous experience with technological change. Leadership support, psychological safety, and cross-functional collaboration facilitate coordinated learning, whereas fragmented governance or competing interpretations may confine learning to isolated organizational units. These alternative pathways reinforce process-theoretical views of organizational change as contingent, recursive, and shaped by generative mechanisms rather than deterministic sequences of events (Pentland, 1999; Langley, 1999).



Figure 4: Diffusion Phase of AI Integration into Talent Acquisition

The outcome of diffusion is not widespread AI adoption but the emergence of organizationally legitimate AI-supported ways of working. Through repeated cycles of experimentation, reflection, adaptation, and coordination, local experimentation becomes organizational routines (Feldman & Pentland, 2003), establishing the conditions for routinization. As illustrated in Figure 4, experimentation and enactment connect the practical testing of AI-supported practices with the calibration of AI outputs and human judgment, workflow re-design, and the negotiation of new human–AI practices, thereby establishing the conditions for routinization.

3.3 Routinization: Embedding AI into Organizational Capability

The routinization phase begins when AI-supported practices are no longer perceived as isolated experiments but become integrated into everyday Talent Acquisition activities. At this stage, the primary challenge shifts from technological implementation to stabilizing patterns of action that enable AI to become a reliable component of organizational capability. Rather than marking the end of AI integration, routinization reflects the institutionalization of practices that have demonstrated organizational value through repeated enactment and collective learning. This understanding is consistent with research showing that organizational routines emerge through repeated performances while providing both stability and opportunities for change (Feldman & Pentland, 2003; Pentland et al., 2012).

As organizations retain successful AI-supported practices, they become embedded in recruitment workflows, governance arrangements, decision-making processes, and professional roles. Standard operating procedures, performance indicators, ethical guidelines, and governance mechanisms increasingly reflect accumulated organizational learning rather than initial implementation decisions. Routinization does not imply rigid standardization. Rather, routines continue to evolve as actors adapt established practices to changing cir-

cumstances, reproducing and modifying organizational capability simultaneously (Feldman & Pentland, 2003). From this perspective, AI-supported routines are continuously enacted and reshaped through organizational practice, reflecting the interaction between digital technologies and everyday work (Orlikowski, 2000).

Reflexive learning becomes the dominant generative mechanism during this phase. Organizational actors evaluate recruitment outcomes, monitor AI performance, identify unintended consequences, and revise practices in response to experience. Routinization of AI does not imply unquestioned reliance on established algorithmic outputs. Organizations must continually reassess when AI recommendations remain appropriate and when human intervention, adjustment, or override is required. Learning extends beyond technological optimization to refining organizational roles, decision responsibilities, governance arrangements, and collaborative practices. Rather than treating implementation as a completed project, organizations transform operational experience into revised routines. This recursive relationship between action, reflection, and routine adaptation represents the microfoundation through which organizational capabilities evolve (Pentland et al., 2012; Teece, 2007).

Routinization does not eliminate uncertainty. Changes in labour markets, regulation, AI technologies, and organizational priorities continually require adaptation. Organizational capabilities therefore remain dynamic rather than permanently stabilized. This perspective aligns with dynamic capability theory, which conceptualizes capabilities as the capacity to integrate, build, and reconfigure organizational resources in response to changing environments rather than as static assets (Teece, 2007; Helfat et al., 2007).

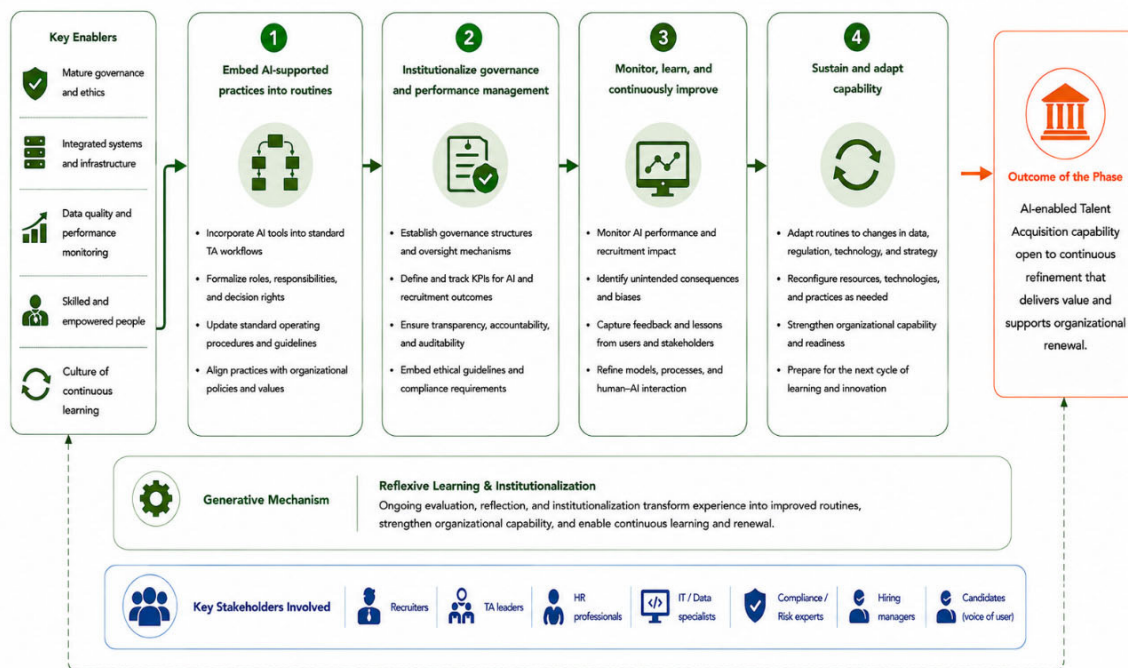


Figure 5: Routinization Phase of AI Integration into Talent Acquisition

The outcome of routinization is the emergence of an AI-enabled Talent Acquisition capability open to continuous refinement. Established routines enhance consistency, coordination, and operational effectiveness while generating new experiences that stimulate further learning. As illustrated in Figure 5, reflexive learning and institutionalization connect the embedding of AI-supported practices with governance, performance monitoring, and the continuous refinement of human-AI practices and organizational capability. Routinization therefore stabilizes AI-enabled Talent Acquisition capability without rendering it static, while creating the conditions for subsequent cycles of sensemaking, experimentation, and organizational renewal.

3.4 Theoretical contributions of the Proposed Process Theory

The proposed narrative process theory contributes to the literature by conceptualizing AI integration as a recursive organizational process through which Talent Acquisition capabilities emerge. Rather than treating AI integration as a technology implementation project, the framework shifts attention to the organizational processes through which AI-enabled work practices are constructed, enacted, and continuously reshaped. In doing so, it responds to calls for stronger process-oriented theorizing explaining how organizational phenomena unfold over time rather than merely identifying antecedents or outcomes (Langley, 1999; Pentland, 1999).

First, the proposed theory extends the emerging literature on AI in Human Resource Management by conceptualizing AI integration as an organizational capability-building process rather than primarily a technology-adoption phenomenon. AI-enabled capabilities emerge through interactions among organizational actors, evolving work practices, and continuous learning, positioning AI as a catalyst for capability development rather than the sole driver of organizational transformation. Second, the framework contributes to process theory by conceptualizing AI integration as recursive rather than linear. Organizational development is explained through the continuous interaction of collective sensemaking, experimentation, and reflexive learning, with routinization representing temporary stabilization that enables subsequent cycles of organizational renewal (Langley, 1999; Feldman & Pentland, 2003). Third, the proposed theory contributes to organizational capability research by explaining the micro-processes through which AI-enabled capabilities develop. Collective sensemaking, distributed experimentation, and reflexive learning function as generative mechanisms linking individual action with organizational capability development, complementing dynamic capability research (Teece, 2007; Helfat et al., 2007). Finally, the framework contributes methodologically by illustrating how narrative process theorizing can be applied to AI-enabled organizational transformation. Rather than explaining change through relationships among static variables, it explains how work practices are generated, negotiated, adapted, and institutionalized over time, providing a framework for future empirical research.

4. AI Integration across the Talent Acquisition process

Talent Acquisition is itself a process comprising interconnected activities through which organizations anticipate workforce needs, attract potential candidates, evaluate talent, make selection decisions, and facilitate entry into the organization. As AI becomes increasingly embedded in HRM, its implications extend beyond technology adoption to broader changes in HR practices and organizational processes (Minbaeva, 2021). As illustrated in Figure 6, AI integration can occur across the Talent Acquisition process, although its role and organizational implications vary considerably between activities. In workforce planning, AI can support forecasting and skills analysis; in employer branding, content development and audience targeting; in candidate sourcing, identification and matching of potential candidates; and in candidate engagement, personalized communication and conversational support. AI may also support candidate assessment and selection through screening, evaluation, and decision support, while job-offer and onboarding activities can incorporate AI-enabled communication, information provision, and personalized support. These applications illustrate the expanding role of AI across recruitment and selection activities (Herold & Roedenbeck, 2025). Thus, AI integration should not be understood as a uniform intervention across Talent Acquisition but as a process whose specific form depends on the activity into which AI is introduced.

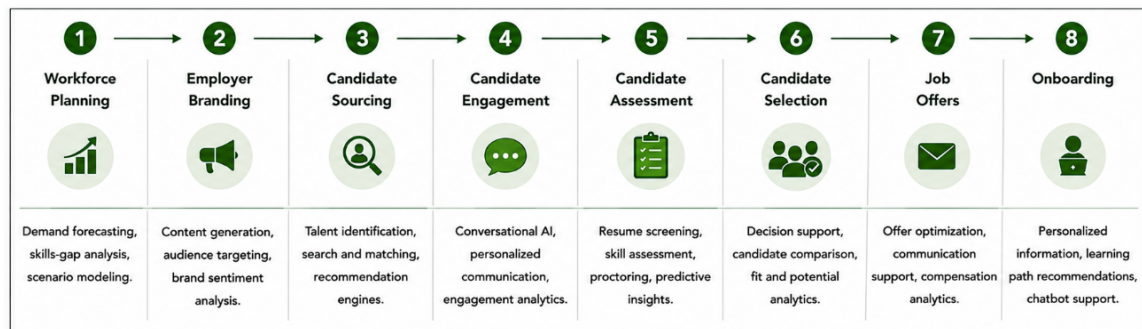


Figure 6: AI Integration Opportunities Across the Talent Acquisition Process.

The process theory developed in Section 3 illustrates how such integration unfolds within particular Talent Acquisition activities, such as candidate sourcing. During Initiation, organizational actors identify sourcing limitations, interpret the potential and risks of AI-supported candidate identification and matching, and establish appropriate boundaries between algorithmic recommendations and recruiter judgment. During Diffusion, recruiters and other stakeholders experiment with AI-supported sourcing, evaluate recommendations, calibrate AI outputs against professional judgment, and adapt workflows through experience. During Routinization, effective practices become embedded in sourcing routines while their performance and consequences continue to be monitored and refined.

The same process may unfold differently in candidate assessment and selection, where decisions have more direct consequences for candidates and therefore require greater attention to fairness, transparency, accountability, and human oversight. Initiation consequently involves more explicit consideration of decision authority and responsible AI boundaries. Diffusion requires systematic evaluation of AI outputs and

their relationship with professional judgment, while Routinization requires governance, monitoring, and mechanisms for human intervention and continued reassessment. These examples illustrate that Initiation, Diffusion, and Routinization provide a common process logic, but their enactment varies across Talent Acquisition activities according to the nature, consequences, and governance requirements of AI use.

Conclusion

Artificial Intelligence is transforming Talent Acquisition, yet existing research provides limited insight into how AI-enabled capabilities emerge through organizational action. This paper develops a narrative process theory that conceptualizes AI integration as a recursive process of Initiation, Diffusion, and Routinization, linked by collective sensemaking, experimentation and enactment, and reflexive learning and institutionalization. The framework contributes to process and organizational capability research by explaining how technological possibilities become organizational capability through interactions among actors, evolving practices, and organizational learning. Consistent with process perspectives (Van de Ven & Poole, 1995; Langley, 1999; Cloutier & Langley, 2020), AI integration is conceptualized as an unfolding rather than linear implementation process. Complementing dynamic capability theory (Teece, 2007; Helfat et al., 2007), the framework identifies collective interpretation, experimentation, and routine adaptation as processes through which AI-enabled capability emerges and evolves.

For organizations, successful AI integration requires collective learning, cross-functional collaboration, effective governance, and AI-supported practices that complement professional expertise (Jarrahi, 2018). As demonstrated across Talent Acquisition activities, the specific requirements for human judgment, governance, and accountability vary according to the context in which AI is integrated. The conceptual framework requires empirical validation through longitudinal and comparative research across organizational contexts and stages of AI maturity. Future research may also examine its applicability to other HRM functions.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this manuscript, ChatGPT (OpenAI) was used solely for language editing, including grammar correction, clarity improvement, and stylistic refinement. All ideas, theoretical framing, analysis, interpretations, and conclusions were developed independently by the author. The author reviewed and approved all revisions and assumes full responsibility for the final manuscript.

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