EP-JOURNALS

Available on: https://jmrr.ep-journals.org/ E-ISSN: 3051-3588, P-ISSN: 3051-357X

Journal of Management Research and Review

Volume: 02 Issue: 07 July-2026

HR Analytics as an Organizational Learning Capability: Dynamic Capabilities, Absorptive Capacity, And Double-Loop Learning

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Published Date: July 22, 2026 **Article DOI: 10.65150/EP-jmrr/V2E7/2026-08**

ABSTRACT

Objective: This article reconceptualises HR analytics from a decision-support tool to an organisational learning capability by integrating three theoretical traditions that have not been jointly mobilised in the HR analytics literature: dynamic capabilities theory, absorptive capacity, and organisational learning theory.

Design/methodology: A theoretical integrative review (Torraco, 2005) synthesizes three bodies of literature through a structured analytical protocol. Published empirical findings from prior studies are reinterpreted under the integrated theoretical lens as secondary empirical anchoring.

Findings: HR analytics maturity activates dynamic HR capabilities (sensing, seizing, reconfiguring) that produce organisational learning only when absorptive capacity mediates the conversion of analytical outputs into actionable knowledge. Learning depth, from single-loop correction to double-loop reconfiguration, determines the strategic quality of human capital decisions. Eight propositions and four contextual moderators are formalised.

Implications: This article offers a novel application, among the first in the HR analytics domain, of the dynamic capabilities-absorptive capacity-organizational learning nexus, shifting the field's guiding question from "What can HR analytics do?" to "How does an organisation learn through HR analytics?"

KEYWORDS: HR analytics, dynamic capabilities, absorptive capacity, organisational learning, double-loop learning, evidence-based HRM

1. INTRODUCTION

A paradox has quietly settled into the HR analytics literature. Organisations invest heavily in analytical technologies, hire data scientists, and build dashboards, yet their measurable impact on strategic human capital decisions remains elusive (Angrave et al., 2016; Marler & Boudreau, 2017; Minbaeva, 2018). Bersin (2021) reported that less than 12% of organisations achieve predictive maturity in workforce analytics, despite a decade of accelerating investment. The paradox is not technological; it is organisational. The tools exist, but the mechanism by which analytical data become organisational knowledge and through which that knowledge transforms decision-making remains theoretically unspecified.

Three scholarly streams have addressed this gap, each illuminating one dimension while leaving others in shadow. The first has catalogued what HR analytics can do, producing typologies that map sophistication levels from descriptive reporting to prescriptive optimisation (Davenport et al., 2010; Falletta and Combs, 2020). The second has examined why adoption falters, identifying barriers such as data quality, analytical skill deficits, and managerial resistance (Angrave et al., 2016; Fernandez and Gallardo-Gallardo, 2021; Tursunbayeva et al., 2018). The third has explored the performance linkage, asking under what conditions analytics deployment translates into measurable organisational outcomes (Levenson, 2018; McCartney and Fu, 2022).

These streams share a structural limitation. They treat HR analytics as a decision-support tool, an input-output mechanism where better data yield better decisions. This framing cannot explain the field's most robust empirical finding: that organisations at comparable levels of analytical sophistication produce radically different outcomes (Belizón et al., 2024; Minbaeva, 2018). If analytics were merely a tool, identical tools would produce equivalent results. They do not; the mechanism between data and decision is not the tool but something internal to the organization, something the prevailing paradigm has yet to theorise.

This article draws on three theoretical traditions that the HR analytics literature has not yet explored to address this gap. Dynamic capability theory (Teece et al., 1997; Teece et al., 2007; Zollo & Winter, 2002) provides a framework for understanding how organisations sense environmental signals, seize opportunities, and reconfigure resources. Absorptive capacity (Cohen and Levinthal, 1990; Zahra and George, 2002) specifies the mechanism by which externally or internally generated knowledge is recognised, assimilated, transformed, and exploited. Organisational learning theory, specifically the single-loop/double-loop distinction (Argyris and Schön, 1978) and the 4I framework (Crossan et al., 1999), defines the depth of knowledge transformation that determines whether analytics corrects operational errors or reconfigures strategic assumptions.

The urgency of this reframing is visible across sectors. In healthcare, analytics platforms that predict nurse turnover fail to reduce it because the insight never reaches the operational decision-makers who schedule shifts (Levenson, 2018). In technology firms, attrition models that identify flight risk with high accuracy do not change retention practice because HR business partners lack the interpretive capacity to translate probability scores into managerial action (Minbaeva, 2018). In manufacturing, workforce planning algorithms that optimise headcount allocation produce recommendations that line managers ignore because the analytical output was developed without their participation (Angrave et al., 2016). In each case, the technology works; organisational learning fails.

This article makes three contributions to HR analytics and strategic HRM literature. First, it repositions HR analytics from a decision-support tool to an operational mechanism through which dynamic capabilities are exercised in human capital management reconceptualisation that the HR analytics domain has not previously undertaken. This is a critical distinction: HR analytics is not itself a dynamic capability but rather the mechanism through which sensing, seizing, and reconfiguration are operationalised in the specific context of workforce management. Second, it introduces absorptive capacity as the mediating mechanism that explains differential outcomes from comparable analytical investments, addressing the field’s inability to explain why identical tools produce divergent results. Third, it formalises the connection between analytical maturity and learning depth, specifying the conditions under which HR analytics enables the transition from single-loop operational correction to double-loop strategic reconfiguration. Connections between dynamic capability, absorptive capacity, and organisational learning exist in the strategic management literature (Zollo and Winter, 2002; Zahra and George, 2002). The contribution here is their first systematic integration within the HR analytics field, where no prior treatment has articulated these three frameworks as an integrated explanatory mechanism.

The article proceeds as follows. Section 2 reviews the three bodies of literature and identifies the unexplored intersection. Section 3 presents the integrative review methodology. Section 4 develops the theoretical framework, propositions, and discusses theoretical and practical implications. Section 5 concludes.

2. LITERATURE REVIEW

2.1. HR Analytics: The Limits of the Decision-Making Paradigm

The term 'HR analytics', used here following Falletta and Combs (2020, p. 54) to designate a systematic process for collecting, analysing, and reporting workforce data to support evidence-based human capital decisions, encompasses the cognate terms 'people analytics', 'workforce analytics', and 'talent analytics'. The field’s intellectual history reveals a progressive expansion of scope coupled with a persistent conceptual constraint.

Fitz-Enz (1980) introduced quantitative measurement to human resources, and subsequent decades saw the development of increasingly sophisticated metrics (Boudreau and Ramstad, 2003, 2007). Davenport et al. (2010) proposed the field’s most influential typology, distinguishing progressively sophisticated functions from human-capital facts through analytical HR to human-capital supply chains. This typology became a template: later frameworks consistently map maturity levels along a descriptive-to-prescriptive continuum (Margherita, 2022).

Marler and Boudreau (2017), in an evidence-based review, found that despite transformative claims, actual HR analytics adoption remained low, and academic research lagged behind practitioner rhetoric. McCartney and Fu (2022) extended this finding, demonstrating that the link between analytics deployment and organisational performance was contingent on poorly understood mediating processes. The fundamental limit of this paradigm is its treatment of analytics as a tool. Tools process inputs into outputs. They do not learn. The consistent finding that organisational context matters more than analytical sophistication (Belizón et al., 2024; Minbaeva, 2018) signals that the missing mechanism is not computational but cognitive and organisational.

2.2. Dynamic Capabilities Theory

The dynamic capabilities framework identifies three organisational process clusters: sensing (identification of opportunities and threats), seizing (mobilisation of resources to capture value), and reconfiguration (continuous renewal of organisational assets and structures) (Teece et al., 1997; Teece, 2007). Zollo and Winter (2002) established the microfoundations connecting learning to capability development, arguing that dynamic capabilities emerge from the co-evolution of deliberate learning mechanisms, including experience accumulation, knowledge articulation, and knowledge codification. Helfat and Peteraf (2003) extended this view by introducing the capability lifecycle, distinguishing founding, development, and maturity stages through which capabilities evolve or decline.

The framework has been applied extensively in strategic management (Schilke et al., 2018) and validated empirically across contexts. Fainshmidt et al. (2016), in a meta-analysis, confirmed significant performance effects of dynamic capabilities moderated by environmental dynamism. Wilden et al. (2013) demonstrated that dynamic capabilities mediate the relationship between organisational structure and performance.

A critical engagement with the framework’s known limitations is necessary. Arend and Bromiley (2009) raised the fundamental objection of conceptual circularity: if dynamic capabilities are defined by their outcomes (superior performance, successful adaptation), the construct becomes tautological. Barreto (2010), in a comprehensive review, documented this circularity and argued for specifying capabilities independently of their performance consequences. Our use of the framework addresses this concern directly. We define the mechanism (HR analytics processes) independent of the outcome (organisational learning), thereby breaking the circular dependency that Arend and Bromiley identified. The analytics function’s sensing, seizing, and reconfiguring activities are specified by their operational content (scanning workforce data, mobilising interventions, and restructuring HR processes) rather than by whether they produce learning. This distinction is central to Proposition 1.

The absence of dynamic capabilities theory from the HR analytics literature is surprising, given the conceptual fit. A mature analytics function scans workplace data environments (sensing), mobilises evidence for HR interventions (seizing), and enables the restructuring of HR processes in response to new patterns (reconfiguring). This mapping has not been formalised in the literature, which has instead treated analytics adoption through technology acceptance models (TAM/UTAUT) better suited to individual-level behaviour than to organisational-level capability development.

2.3. Absorptive Capacity

Cohen and Levinthal (1990) defined absorptive capacity as the ability to recognise new information's value, assimilate it, and apply it to commercial ends. Zahra and George (2002) reconceptualised the construct as four dimensions organised in two sequential components: potential absorptive capacity (acquisition and assimilation) and realised absorptive capacity (transformation and exploitation). The potential-to-realised conversion is neither automatic nor guaranteed; it depends on social integration mechanisms (cross-functional teams, shared mental models, and knowledge-bridging roles) that translate acquired knowledge into organisational action.

The construct, for all its theoretical power, has faced legitimate methodological critique. Lane et al. (2006) argued that absorptive capacity had been reified, treated as a static organisational attribute rather than as a dynamic process. They called for research that examines how absorptive capacity unfolds over time rather than measuring it through proxies such as R&D expenditure or patent counts. Volberda et al. (2010) extended this critique, showing that the concept had been "absorbed" into management research without sufficient attention to its multi-level nature or its processual dynamics. These critiques are relevant here because HR analytics presents a domain where absorptive capacity operates through specific, observable mechanisms (interpretive routines, translation roles, and cross-functional analytics meetings) rather than through the distant proxies that have troubled measurement in other contexts. This specificity is both an advantage and a challenge: it offers operationalisation potential but requires validation against the processual standard that Lane et al. advocated.

Applied to HR analytics, the framework maps precisely. When an analytics team produces a turnover prediction, that output must be acquired by decision-makers (who must encounter it), assimilated (understood in relation to existing HR knowledge), transformed (connected to actionable HR interventions), and exploited (embedded in operational practice). Flatten et al. (2011) developed and validated a multi-dimensional scale for absorptive capacity that aligns with these processes. The recurrent finding that analytics fails not because of poor data but because of poor translation (Angrave et al., 2016) is, in terms of absorptive capacity, a failure of conversion from potential to realised capacity.

2.4. Organisational Learning: Single-Loop and Double-Loop

Argyris and Schön (1978) drew a distinction whose relevance to HR analytics has not been adequately theorised. Single-loop learning corrects errors without altering the underlying assumptions, norms, or objectives that caused them. Double-loop learning restructures those assumptions themselves. Huber (1991) systematised the contributing processes of organisational learning, identifying knowledge acquisition, information distribution, information interpretation, and organisational memory as the core sub-processes through which learning occurs at the collective level.

Crossan et al. (1999), in a seminal contribution, proposed the 4I framework, linking individual-level intuiting and interpretation to group-level integrating and institutional-level institutionalising. This multi-level model captures a tension central to our argument: insights that emerge from analytical processes at the individual or team level must traverse organisational levels to become institutionalised practice; this traversal is subject to resistance, distortion, and loss. Nonaka and Takeuchi (1995) complemented this perspective through the SECI model (socialisation, externalisation, combination, and internalisation), which specifies how tacit knowledge becomes explicit and how explicit knowledge becomes embedded in organisational practice.

A dimension that is largely absent from standard organisational learning models is the political aspect. Argyris (1990) himself recognised that defensive routines, the organisational habits that protect individuals and groups from embarrassment or threat, constitute the principal obstacle to double-loop learning. When HR analytics reveals that a long-standing talent management practice is ineffective, the insight threatens the professional identity and authority of those who championed that practice. The transition from single-loop to double-loop learning is, in this reading, not only a cognitive challenge (understanding new information) but a political one (overcoming the resistance of actors whose interests are served by existing assumptions). Crossan et al.'s (1999) framework acknowledges feed-forward and feedback tensions between organisational levels but does not fully theorise the power dynamics that accelerate or obstruct the institutionalisation of learning. We integrate this political dimension as a boundary condition rather than a core mechanism, acknowledging its importance while recognising that the full political theory of analytics-driven learning exceeds the scope of this article.

Applied to HR analytics, the single-loop/double-loop distinction maps onto observable differences in practice. Descriptive analytics operates within single-loop logic: monitoring metrics, detecting deviations, and triggering corrective actions within established frameworks. When a dashboard flags rising absenteeism, the corrective response (adjusting workloads, enhancing wellness programmes) occurs within existing operational parameters. Predictive and prescriptive analytics carry the potential for double-loop learning. A model revealing that high-performer attrition correlates with managerial behaviour rather than compensation challenges is not just an operational parameter but the underlying assumption about what drives retention, demanding a reconfiguration of the HR decision framework itself. March (1991) framed the issue as the tension between exploitation (refining existing competencies) and exploration (developing new ones); the single-loop/double-loop distinction specifies the learning mechanism through which organisations navigate that tension.

2.5. The Unexplored Intersection

The gap can be stated precisely. The HR analytics literature has established what analytics can do (typologies), why organisations adopt it (drivers and barriers), and whether it improves performance (contingent linkages). It has not explained how analytics generates organisational knowledge or the mechanism by which workforce data move through organisational processes and emerge as strategic insight capable of transforming human capital decisions. Dynamic capabilities theory can explain organisational processes (sensing, seizing, reconfiguring) but not the conversion mechanism that translates analytical output into strategic knowledge. Absorptive capacity can explain the conversion mechanism but not the process architecture through which it operates in the specific context of human capital management. Organisational learning theory can characterise the depth of knowledge transformation, but it does not explain the conditions under which analytics triggers one depth rather than another.

The general strategic management literature connects these three frameworks. Zollo and Winter (2002) established learning mechanisms as micro-foundations of dynamic capabilities. Zahra and George (2002) linked absorptive capacity to dynamic capability development. The contribution of this article is not the connection itself, which exists in the broader literature, but its first systematic application to the HR analytics domain. This application is not merely illustrative; the HR analytics context introduces specific features, the role of HR professionals as knowledge translators, the political sensitivity of workforce data, and the tension between descriptive operational monitoring and predictive strategic insight that require the integrated framework to be specified in ways the general literature has not demanded.

3. METHODOLOGY

This article adopts a theoretical integrative review methodology (Torraco, 2005), which synthesises existing theoretical and empirical work across distinct literatures to generate new conceptual frameworks. The integrative review is distinct from a systematic literature review, which aims for comprehensive coverage of a defined field, and from a meta-analysis, which statistically aggregates empirical effect sizes. It is suited to contexts where multiple mature texts require reconceptualisation rather than additional accumulation and where the central contribution is theoretical synthesis rather than empirical discovery. Charlwood and Guenole (2022) employed a comparable approach in their theoretical treatment of AI paradoxes in HRM, as did Raisch and Krakowski (2021), who theorised the automation-augmentation paradox.

Three bodies of literature were interrogated through searches in Web of Science, Scopus, ABI/Inform, and PsycINFO, covering the period 1978 to 2025. The first corpus used the search terms “HR analytics” OR “people analytics” OR “workforce analytics” OR “human capital analytics". The second used “dynamic capabilities” AND (“sensing” OR “seizing” OR “reconfiguring”). The third combined “absorptive capacity” AND “organisational learning” OR “double-loop learning". Inclusion criteria required peer-reviewed journal articles, foundational book chapters, and published meta-analyses. Industry reports were included selectively where they provided empirical data not available in academic sources. Table 1 presents the key sources mobilised for integrative synthesis.

Table 1. Key Sources Analysed in the Integrative Review

Reference	Type	Key Constructs	Contribution to Framework
Teece et al. (1997)	Theoretical	Sensing, seizing, reconfiguring	Foundational DC process architecture
Teece (2007)	Theoretical	DC micro-foundations	Specifies managerial processes underlying DC
Zollo and Winter (2002)	Theoretical	Deliberate learning, DC evolution.	Establishes learning as DC micro-foundation
Cohen and Levinthal (1990)	Theoretical	Absorptive capacity	Knowledge recognition, assimilation, application
Zahra and George (2002)	Theoretical	Potential vs. realised ACAP	Mediating conversion mechanism
Lane et al. (2006)	Critical review	Process-based ACAP	Critique of reification; processual reframing
Argyris and Schön (1978)	Theoretical	Single-loop, double-loop learning	Learning depth typology
Crossan et al. (1999)	Theoretical	4I framework (intuiting-institutionalising)	Multi-level learning dynamics
Nonaka and Takeuchi (1995)	Theoretical	SECI model	Tacit-explicit knowledge conversion.
Huber (1991)	Theoretical	OL sub-processes	Knowledge acquisition, distribution, interpretation
Davenport et al. (2010)	Empirical	HR analytics maturity typology	Six-level sophistication framework
Marler and Boudreau (2017)	Evidence-based review	Adoption-outcome gap	Documents rhetoric-reality gap.
McCartney and Fu (2022)	Integrative review	Analytics-performance contingencies	Identifies mediating processes
Minbaeva (2018)	Conceptual/empirical	Credible analytics, strategic integration	Organisational conditions for analytics value
Angrave et al. (2016)	Conceptual	HR skill deficit, analytics failure	Translation failure as capability gap
Belizón et al. (2024)	Qualitative	Knowledge discovery in HR analytics	Documents analytics as a learning process
Fainshmidt et al. (2016)	Meta-analysis	DC-performance link	Effect sizes and environmental moderators
Arend and Bromiley (2009)	Critical review	DC circularity	Tautology critique of DC theory
Volberda et al. (2010)	Critical review	ACAP reification	Multi-level and processual critique

The analytical strategy proceeded in three stages. In the first stage, each piece of literature was analysed independently to identify core constructs, established relationships, recognised limitations, and open questions. In the second stage, structural homologies across the three frameworks were identified: the parallel between sensing and knowledge acquisition, between seizing and knowledge transformation, between reconfiguring and knowledge exploitation, and between absorptive capacity conversion and learning depth transition. In the third stage, these homologies were synthesised into an integrated framework, and propositions were derived from the logical intersections of the three literatures, anchored in reinterpreted empirical evidence from prior studies.

An epistemological clarification is warranted. This paper is a theoretical conceptual article. The propositions advanced are grounded in secondary empirical evidence: findings published in studies designed to answer other research questions, reinterpreted here under the integrated theoretical lens. This approach follows an established tradition in management theory development (Whetten, 1989). This article does not empirically validate the propositions; instead, they form a testable theoretical architecture that future research should prioritise for empirical examination.

4. RESULTS AND DISCUSSION

The integrative review yields a three-component theoretical framework linking HR analytics maturity, dynamic HR capabilities, absorptive capacity, and organisational learning depth. This section develops the framework through four sub-sections, each advancing formal propositions, and concludes with the integrative conceptual model.

4.1. HR Analytics as a Dynamic Capability Mechanism

We contend that HR analytics, when sufficiently mature, serves as the operational mechanism for exercising dynamic capabilities in human capital management. The distinction between mechanism and capability is not semantic; it is theoretically consequential. A capability is an organisational capacity to perform a particular activity reliably (Winter, 2003). A mechanism is the process through which that capacity is enacted. HR analytics does not constitute a dynamic capability because dynamic capabilities reside in managerial and organisational processes, not in tools (Teece, 2007). Analytics provides the informational infrastructure through which sensing, seizing, and reconfiguring become empirically grounded rather than intuition-driven.

In pre-analytics HR practice, sensing occurred informally: managers noticed trends through observation, exit interviews revealed themes retrospectively, and satisfaction surveys captured attitudinal snapshots at fixed intervals. Analytics transforms sensing by enabling continuous, multi-source environmental scanning: real-time monitoring of turnover predictors, network analysis of collaboration patterns, and predictive modelling of workforce supply-demand gaps. Seizing is enacted when analytical insights drive targeted interventions: an evidence-based redesign of compensation structures, data-informed succession planning, or algorithmically optimised scheduling. Reconfiguring occurs when analytical evidence triggers structural change: the reorganisation of HR service delivery models, the redesign of performance management architectures, or the transformation of talent acquisition strategies in response to labour market pattern shifts.

The relationship between analytical maturity and dynamic capability activation is conditional, not automatic. Dynamic capabilities do not activate when analytical teams operate in isolation from HR business partners, regardless of their technical sophistication. Reactive deployment, where analytics is adopted for compliance or mimetic purposes rather than strategic intent, similarly fails to produce capability activation because the sensing-seizing-reconfiguring cycle requires purposeful engagement with analytical outputs.

Proposition 1. HR analytics maturity activates dynamic HR capabilities (sensing, seizing, reconfiguring) only when two conditions are jointly satisfied: (a) the analytical function maintains structural connections to HR decision-makers, and (b) deployment is purposeful rather than reactive. In the absence of either condition, increased analytical sophistication does not produce dynamic capability activation. **Boundary conditions:** This relationship does not hold when analytics is deployed solely for regulatory compliance, when analytical outputs are not routinely accessed by HR decision-makers, or when the analytical function lacks formal channels to operational HR leadership.

4.2. The Mediating Role of Absorptive Capacity

Dynamic capability activation is necessary but insufficient for strategic value creation. Between analytical output and organisational learning lies a conversion process that absorptive capacity theory illuminates with precision (Zahra and George, 2002). The potential to realise conversion distinguishes organisations that acquire analytical knowledge from those that exploit it.

The mediating role operates through four processual dimensions. Analytical outputs must first be acquired by decision-makers, which requires organisational routines that direct analytical products toward relevant audiences. Assimilation demands that recipients possess sufficient prior knowledge to interpret statistical outputs, predictive scores, and prescriptive recommendations in context. Transformation turns assimilated knowledge into actionable HR interventions by connecting analytical patterns to the organisation's specific talent management challenges. Exploitation embeds transformed knowledge into operational routines, updating standard practices in response to analytical evidence.

Social integration mechanisms govern the potential-torealise conversion (Zahra and George, 2002). Cross-functional interpretive routines serve as the primary conversion mechanism, involving regular structured sessions where analytics teams and HR decision-makers jointly examine analytical outputs. Translation roles facilitate the assimilation and transformation stages by bridging the analytical and managerial communities with competencies in both domains. Shared mental models, developed through repeated collaborative interpretation, reduce the cognitive distance between data-oriented and practice-oriented logics.

Proposition 2: Organisational absorptive capacity mediates the relationship between HR analytics-activated dynamic capabilities and organisational learning outcomes. Organisations with higher absorptive capacity convert a greater proportion of analytical capability into realised learning.

Proposition 3. The conversion from potential to realised absorptive capacity in the HR analytics context is determined by the frequency and quality of cross-functional interpretive routines and by the presence of translation roles bridging analytical and managerial communities.

Observable indicators: frequency of scheduled analytics review meetings, existence of designated analytics translator roles, proportion of analytical outputs discussed in cross-functional settings.

4.3. From Data Processing to Knowledge Creation: Learning Depth

Learning depth is not a fixed property of the analytics tool but an emergent outcome of the interaction between analytical maturity and realised absorptive capacity. Single-loop learning can occur with modest absorptive capacity because it identifies deviations and triggers corrective actions within existing frameworks without challenging prevailing assumptions. The HR team that monitors absenteeism dashboards and adjusts staffing levels operates within single-loop logic regardless of analytical sophistication.

Double-loop learning, where analytics challenges the assumptions governing HR decision-making, requires high analytical maturity combined with high realised absorptive capacity. When a predictive model reveals that a compensation structure optimised for individual performance is destroying team collaboration, the organisation faces a double-loop challenge: the insights demand not an adjustment within the existing framework but a reconfiguration of the framework itself. This transition requires not only cognitive capacity to understand insight (absorptive capacity) but also organisational tolerance for disagreement and the political legitimacy of analytical evidence (Argyris, 1990). Defensive routines, the organisational habits that protect established assumptions from challenges, constitute the principal barrier to double-loop learning in analytically mature organisations.

Proposition 4: The depth of organisational learning from HR analytics is jointly determined by analytical maturity and realised absorptive capacity, with the transition from single-loop to double-loop learning additionally requiring organisational tolerance for assumption-challenging evidence and the political legitimacy of analytical insights. Boundary conditions: in organisations where defensive routines are strong and analytical insights lack political sponsorship, high maturity and absorptive capacity produce single-loop learning only.

4.4. Contextual Moderators

Four contextual moderators condition the proposed relationships. Each is specified with its moderated link and theorised mechanism.

Data-driven culture, defined as the normative orientation toward evidence-based decision-making embedded in organisational values and reinforced through management practices, moderates the relationship between analytical maturity and dynamic capability activation (P1). In cultures where intuition and seniority dominate decision norms, even sophisticated analytical outputs fail to trigger sensing-seizing-reconfiguring cycles because the outputs lack legitimacy. Dahlbom et al. (2019) documented that cultural resistance to data-driven approaches was a primary obstacle to analytics value realisation across Finnish organisations.

Proposition 5a. Data-driven organisational culture positively moderates the relationship between HR analytics maturity and dynamic capability activation (P1), such that the activation threshold is lower in cultures where evidence-based reasoning is normatively valued.

HR professional competencies encompass both analytical skills (the ability to interpret statistical outputs) and translational skills (the ability to reframe analytical insights in strategic management terms). Angrave et al. (2016) attributed the analytics-value gap partly to the HR profession’s skill deficit in both domains. This moderator operates on absorptive capacity mediation (P2-P3): skilled HR professionals accelerate the potential-torealise conversion by functioning as social integration mechanisms.

Proposition 5b. HR professional competencies (analytical and translational) positively moderate the mediating effect of absorptive capacity (P2) by accelerating the conversion from potential to realised absorptive capacity through enhanced assimilation and transformation of analytical outputs.

Top management support operates not merely as a resource-allocation mechanism but as a legitimacy function. When senior leaders visibly endorse analytical evidence as a basis for strategic HR decisions, they signal that challenging established assumptions based on data is organisationally sanctioned. This moderator conditions the learning depth relationship (P4): without top management legitimation, analytical insights that challenge prevailing frameworks encounter defensive routines without political sponsorship.

Proposition 5 c. Top management support positively moderates the relationship between absorptive capacity and double-loop learning depth (P4) by providing political legitimacy for assumption-challenging analytical insights and reducing the effectiveness of organisational defensive routines.

Analytical infrastructure encompasses the technical platform (data quality, integration, and accessibility) and the organisational architecture for analytics (centralised versus embedded teams, reporting structures, and data governance). This moderator conditions the foundational relationship (P1): inadequate infrastructure creates a ceiling on analytical maturity regardless of investment, preventing the threshold sophistication necessary for dynamic capability activation.

Proposition 5d. Analytical infrastructure quality positively moderates the relationship between HR analytics maturity and dynamic capability activation (P1) by setting the ceiling on achievable maturity and thereby determining whether the sophistication threshold for capability activation can be reached.

4.5. Integrative Conceptual Model

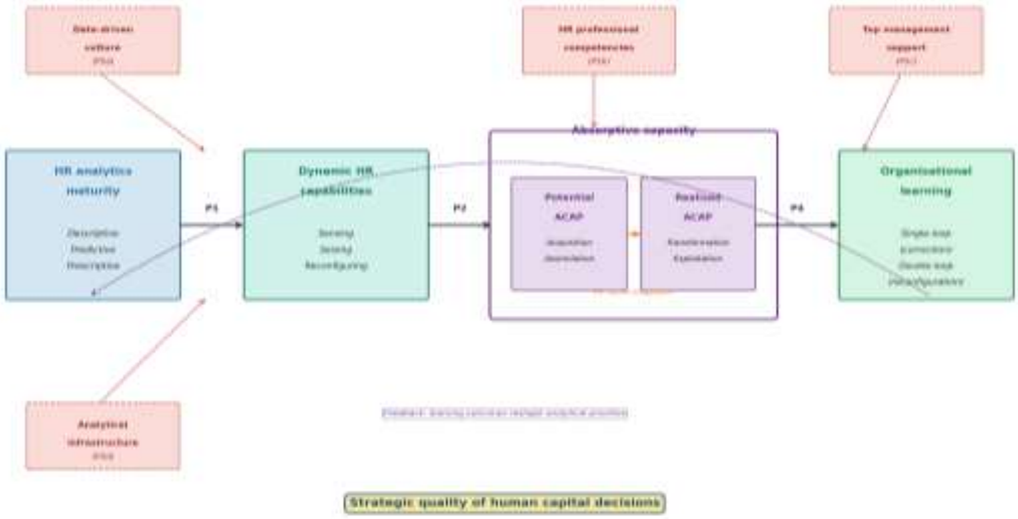

Figure 1. Integrative Conceptual Model: HR Analytics as an Organisational Learning Capability

4.6. Secondary Empirical Reinterpretation

Table 2. Reinterpretation of Published Empirical Findings Under the Integrated Framework

Study	Original Findings	Reinterpretation	Proposition(s)	Limits
Minbaeva (2018)	Analytics credibility requires strategic HRM integration.	Strategic integration constitutes the structural connection enabling DC activation.	P1	Single-case conceptual, not empirically tested across contexts
Angrave et al. (2016)	HR skill deficits prevent analytics value.	A skill deficit represents low ACAP: inability to assimilate and transform analytical outputs.	P2, P5b	Conceptual argument; no quantitative measurement of skill gap
Belizón et al. (2024)	HR analytics operates as a knowledge discovery process.	Knowledge discovery maps onto the ACAP potential-to-realised conversion cycle.	P2, P3	Single-country qualitative; generalisability uncertain.
McCartney and Fu (2022)	Performance link contingent on mediating processes	Mediating processes identified as ACAP dimensions operating between DC and learning.	P2, P4	Review: not primary empirical evidence
Dahlbom et al. (2019)	Cultural resistance blocks analytics value.	Culture moderates the maturity-DC activation link by conditioning evidence legitimacy.	P5a	Nordic context: cultural specificity limits transferability.
Levenson (2018)	Analytics fail when insights do not reach decision-makers.	Failure located in ACAP acquisition dimension: outputs not acquired by relevant audiences	P2, P3	Single-sector focus (healthcare); mechanism inferred
Fainshmidt et al. (2016)	DC effects moderated by environmental dynamism	Environmental dynamism conditions the urgency and speed of reconfiguring processes.	P1	Meta-analysis at the firm level; HR-specific DC not isolated

4.7. Summary of Propositions

Table 3. Summary of Formal Propositions

Prop.	**Statement**	**Theoretical Basis**	**Boundary Conditions**	**Suggested Operationalisation**
P1	Analytics maturity activates DC only when structurally connected to decision-makers and purposefully deployed.	Teece (2007); Zollo and Winter (2002).	Does not hold under reactive/compliance-driven adoption or structural disconnection	Analytics maturity scale; DC activation indicators; structural connectivity index
P2	ACAP mediates the DC-to-learning relationship.	Zahra and George (2002); Cohen and Levinthal (1990).	Requires a minimum threshold of prior HR knowledge among decision-makers.	Flatten et al. (2011) ACAP scale adapted to HR: mediation testing via PLS-SEM.
P3	Potential-to-realised ACAP conversion depends on cross-functional routines and translation roles.	Zahra and George (2002); Lane et al. (2006).	Less effective in highly siloed organisations	Frequency of interpretive meetings, presence of translator roles, and proportion of outputs discussed cross-functionally
P4	Learning depth jointly determined by maturity, realised ACAP, tolerance for disagreement, and political legitimacy	Argyris and Schön (1978); Crossan et al. (1999); Argyris (1990)	Strong defensive routines are limited to single-loop regardless of maturity/ACAP.	Single vs. double-loop classification of HR decisions: defensive routine scale
P5a	Data-driven culture moderates the maturity-DC link.	Dahlbom et al. (2019)	May vary across national cultural contexts	Organisational culture survey; evidence-based decision norm scale
P5b	HR competencies moderate the ACAP mediation.	Angrave et al. (2016)	Competency type (analytical vs. translational) may have differential effects.	HR analytics competency assessment; translational skill inventory
P5c	Top management support moderates the ACAP-learning depth link.	Argyris (1990)	Symbolic support without resource commitment may be insufficient.	TMT analytics sponsorship index: resource allocation patterns
P5d	Analytical infrastructure moderates the maturity-DC link.	Davenport et al. (2010)	Infrastructure is necessary but not sufficient; ceiling effect expected	Data quality index; integration maturity; platform capability assessment

4.8. Theoretical Contributions

This article's contribution is straightforward: HR analytics is not a tool but an organisational learning mechanism whose effectiveness depends on absorptive capacity. This statement integrates three theoretical traditions that, while connected to the broader strategic management literature (Zollo and Winter, 2002; Zahra and George, 2002), have not been jointly mobilised to explain how HR analytics generates strategic value.

The first contribution repositions analytics from instrument to capability mechanism. The prevailing paradigm in HR analytics research treats the analytical system as an input-output device: data enters, insights emerge, and decisions improve. Our framework reveals the model as incomplete. The analytical system is the operational mechanism through which dynamic capabilities are exercised, but the conversion of mechanism output into organisational learning depends on an intervening process, absorptive capacity, that the 'tool' metaphor entirely obscures. This repositioning aligns HR analytics with the dynamic capabilities tradition (Teece, 2007) while avoiding the tautological error of equating capability with outcome, which was critiqued by Arend and Bromiley (2009).

The second contribution specifies why identical analytical investments produce divergent outcomes. Absorptive capacity, operating through the potential-to-realised conversion mechanism (Zahra and George, 2002), explains the variance. Two organisations with equivalent Tableau dashboards and identical predictive models will generate different strategic values to the extent that their social integration mechanisms, translation roles, and cross-functional routines differ. This is a testable explanation for the field's most persistent empirical puzzle.

The third contribution formalises the connection between analytical maturity and learning depth. The single-loop/double-loop distinction (Argyris and Schön, 1978), enriched by Crossan et al.'s (1999) multi-level dynamics and the political dimension Argyris (1990) identified, provides a typology of learning outcomes that existing HR analytics frameworks lack. The proposition that double-loop learning requires not only analytical sophistication and absorptive capacity but also organisational tolerance for disagreement and political sponsorship adds a dimension absent from the predominantly rational-cognitive models in the field.

4.9. Repositioning HR Analytics in Strategic HRM

The evidence-based management perspective (Rousseau, 2006; McCartney and Fu, 2022) positions analytics as a tool supporting rational decision-making. Our framework accepts this positioning as a starting point but argues it captures only single-loop learning: analytics supports better decisions within existing frameworks. The strategic potential of HR analytics lies in its capacity to trigger double-loop learning, the reconfiguration of the frameworks themselves.

4.10. Practical Implications

For practitioners, the central message is direct: technology investment without absorptive capacity investment is wasted. Organisations allocating budgets to analytics platforms while neglecting the interpretive infrastructure, cross-functional routines, translation roles, and shared mental models that convert analytical output into organisational learning will reproduce the documented pattern of sophisticated dashboards that change nothing (Angrave et al., 2016; Minbaeva, 2018).

A second implication concerns sequencing. Analytics maturity progression should be gated by absorptive capacity readiness. An organisation whose HR team cannot interpret descriptive statistics will be unable to benefit from predictive modelling, regardless of platform capability. Climbing the maturity staircase (Davenport et al., 2010) should occur simultaneously with the development of absorptive capacity, not in advance.

A third implication differs by organisational context. In large organisations with established analytics functions, the priority is conversion, building the social integration mechanisms that translate analytical potential into realised learning. In small and medium enterprises, where analytical resources are constrained, the priority is building foundational absorptive capacity, the HR team's interpretive competence, before investing in analytical sophistication. The framework suggests a leapfrogging opportunity for organisations in emerging economies, where HR analytics adoption is still in its early stages and formal HR practices may be less established. Rather than replicating the maturity staircase of advanced economy organisations, emerging economy firms can invest in absorptive capacity first, building interpretive and translational competencies that position the organization to extract strategic value from analytics when it is introduced, thereby bypassing the documented pattern of technology-first, capability-second adoption. This sequencing is particularly relevant in African contexts, where institutional features such as informal HR practices, constrained data infrastructure, and reliance on relational rather than procedural management create distinctive boundary conditions for the proposed model (Kamoche, 2011).

4.11. Limitations

Six limitations warrant transparent acknowledgement. First, the propositions advanced are untested empirically. They constitute a theoretical architecture that requires validation through primary data collection. The framework's value is heuristic and generative at this stage, not confirmatory.

Second, the empirical anchoring relies on secondary evidence: findings from studies designed for other purposes, reinterpreted under the integrated theoretical lens. This approach carries an inherent risk of confirmation bias. Findings consistent with our framework have been selected; contradictory evidence may exist in literature not surveyed. The reinterpretations in Table 2 should be read as plausibility demonstrations, not as empirical tests.

Third, a residual circularity risk attends the dynamic capabilities component. Although we define the mechanism (analytics) independently of the outcome (learning), the empirical measurement of dynamic capability activation remains challenging. Researchers operationalising Proposition 1 must ensure that activation indicators do not collapse into outcome measures, a known difficulty in the dynamic capabilities literature (Barreto, 2010).

Fourth, the model is predominantly cognitive and rational. The political dimension of organisational learning, acknowledged through Argyris's (1990) defensive routines and integrated as a boundary condition in Proposition 4, is not theorised as a core mechanism. Power dynamics, interest conflicts, and resistance to analytical evidence are likely to shape the learning process in ways the framework does not fully capture. A comprehensive political theory of analytics-driven learning remains a task for future research.

Fifth, the sources mobilised are primarily drawn from North American and European research contexts. The framework's applicability to institutionally distinct settings in Asia, Africa, and Latin America, where HR practices, organisational cultures, and data environments differ substantially, is an open empirical question.

Sixth, the model assumes purposeful deployment of HR analytics. When institutions adopt HR analytics due to mimicry, regulatory compliance, or vendor pressure instead of strategic intent, the learning dynamics outlined in the framework may not activate, as acknowledged by Proposition 1's boundary conditions.

4.12. Future Research Agenda

Three research directions emerge from the theoretical framework, each specified with sufficient operational detail to guide empirical investigation.

The first direction is the quantitative validation of the mediation chain through structural equation modelling. A PLS-SEM design (Hair et al., 2019) is appropriate given the theory's exploratory stage. The endogenous variable would be organisational learning depth, operationalised as the proportion of HR decisions classified as double-loop (framework reconfiguration) versus single-loop (error correction). The mediating variable, absorptive capacity, would be measured using Flatten et al.'s (2011) validated four-dimensional scale adapted to the HR analytics context. The exogenous variable, HR analytics maturity, would be captured through the Davenport et al. (2010) typology, which is operationalised as a Likert-based self-assessment. The moderators (culture, competencies, support, infrastructure) would be measured using established scales and tested as interaction effects. The target sample would include organisations with varying maturity levels across multiple industries in at least two institutional contexts (e.g., a coordinated market economy and a liberal market economy). With this model complexity, a minimum sample of 200 organisations would be required for adequate statistical power in PLS-SEM.

The second direction is qualitative longitudinal research on the absorptive capacity conversion process. A multiple-case design (Yin, 2018) following six to eight organisations introducing predictive HR analytics over a 12- to 18-month period would capture the temporal dynamics of the potential to realise conversion. Data collection through interviews with analytics teams, HR business partners, and line managers at three-month intervals, complemented by document analysis of analytics reports and HR decision records, would reveal the social integration mechanisms through which analytical outputs are (or are not) converted into organisational learning. The Gioia et al. (2013) methodology would enable systematic coding of first-order informant categories and second-order theoretical themes, with the integrated framework guiding abductive analysis.

The third direction is comparative institutional research on boundary conditions. The framework's propositions are specified without explicit institutional conditioning, yet the moderating effects are likely to vary across institutional contexts. In coordinated market economies with strong worker representation (Germany, the Netherlands, and Nordic countries), collective voice mechanisms may accelerate the potential-to-realised ACAP conversion by creating structured forums for analytical evidence interpretation. In liberal market economies with weaker institutional protections, conversion may depend more heavily on managerial initiative. In emerging economies, particularly in African contexts where institutional voids and informal HR practices create distinctive conditions, the model's assumptions about formal analytical infrastructure and structured absorptive capacity mechanisms may require modification. A multi-country survey design with matched samples across three institutional types would enable moderated mediation testing of these institutional effects.

5. CONCLUSION

How does an organisation learn from HR analytics? The answer this article offers requires integrating three theoretical traditions that the HR analytics field has kept separate. HR analytics maturity activates dynamic HR capabilities by transforming workforce sensing, seizing, and reconfiguring from intuition-driven to evidence-driven processes. Activation produces organisational learning only to the extent that absorptive capacity mediates the conversion of analytical outputs into actionable knowledge. The depth of that learning, whether it corrects operational errors within existing frameworks or reconfigures the frameworks themselves, depends on the joint level of analytical maturity and realised absorptive capacity, conditioned by political legitimacy and organisational tolerance for assumption-challenging evidence.

The framework's central implication is that the field has been asking a partial question. "What can HR analytics do?" treats analytics as a tool and produces typological answers. "How does an organisation learn through HR analytics?" treats analytics as a mechanism embedded in organisational processes and demands attention to the absorptive, political, and cultural conditions that determine whether analytical sophistication translates into strategic knowledge. The shift from the first question to the second is the shift this article advocates.

Organisations treating HR analytics as a technology problem will continue producing the documented pattern: sophisticated platforms generate insights that nobody uses. Organisations treating HR analytics as a learning capability will invest in the interpretive infrastructure, the cross-functional routines, the translation roles, and the political sponsorship that converts data into knowledge and knowledge into transformed practice. The theoretical framework developed here provides a conceptual architecture for understanding why this difference exists and, in its propositions, a testable program for explaining when and how it can be overcome.

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