Center for Management Science Research
ISSN: 3006-5291 3006-5283 Volume 4, Issue 3, 2026

THE IMPACT OF HR ANALYTICS CAPABILITIES ON EMPLOYEE INNOVATION: THE MEDIATING ROLE OF TALENT MANAGEMENT EFFECTIVENESS AND THE MODERATING ROLE OF TOP MANAGEMENT SUPPORT

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DOI: https://doi.org/10.5281/zenodo.24028658

Keywords
HR analytics capabilities; employee innovation; talent management effectiveness; top management support; mediation; moderation

Article History
Received: 01 January 2026
Accepted: 07 March 2026
Published: 30 March 2026

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Abstract
Organisations are investing heavily in HR analytics, yet how it translates into employee innovation remains *poorly understood. Drawing on the resource-based view, dynamic capabilities theory, the ability–motivation–opportunity framework and the technology–organisation–environment framework, this study tests whether talent management effectiveness mediates the link between HR analytics capabilities and employee innovation, and whether top management support moderates the link between HR analytics capabilities and talent management effectiveness. A cross-sectional survey of HR professionals, managers and employees in mid- to large-sized firms yielded 112 usable responses. Established multi-item scales showed good internal consistency (Cronbach's α = .809–.969). Hypotheses were tested using ordinary least squares regression, bias-corrected bootstrapped mediation analysis (5,000 resamples) and hierarchical moderated regression. HR analytics capabilities predicted employee innovation (β = .84, p < .001) and talent management effectiveness (β = .86, p < .001), and talent management effectiveness predicted employee innovation (β = .89, p < .001). The indirect effect through talent management was significant (effect = 0.60, 95% CI [0.43, 0.77]) while the direct effect remained significant, indicating partial mediation. Top management support did not moderate the analytics–talent management relationship (b = −0.05, p = .384), although it was a strong direct predictor of talent management effectiveness. The findings suggest that HR analytics fosters innovation mainly by strengthening the talent system, and that leadership support adds to, rather than amplifies, its effect. Theoretical and managerial implications, limitations and directions for future research are discussed.*

1. INTRODUCTION

Organisations today must compete not only on products and markets but also on how well they use data at every level of decision making, and the human resource (HR) function is no exception. Traditionally driven by administrative routine and professional intuition, HR is now expected to demonstrate strategic value through the systematic use of workforce data (Marler & Boudreau, 2017). HR analytics, the systematic collection, analysis and interpretation of employee data, is central to this shift because it promises people decisions grounded in evidence rather than guesswork (Zebua et al., 2024).

The evidence suggests that this value is real but conditional. Small Zimbabwean firms that combined analytics with high-performance work practices reported substantial productivity gains (Muchowe et al., 2025), and strategic intelligence explained more than half of the variation in organisational excellence among Jordanian institutions (Maqableh & Al-Shawabkeh, 2025). In contrast, Noor et al. (2025) found that HR analytics did not significantly improve talent management or HR decision making in Bangladeshi firms, attributing the null result to weak leadership engagement, an immature data culture and limited infrastructure and skills. Analytics, in other words, is only as valuable as the internal processes that carry its insight into behaviour and the context in which it operates.

Two gaps follow. First, although talent management is a plausible bridge between analytical insight and employee outcomes, the mechanism linking HR analytics to employee innovation is seldom modelled and tested directly (Marler & Boudreau, 2017; Noor et al., 2025). Second, top management support is more often advocated than measured as a boundary condition. Without this account, organisations risk buying analytics tools that never translate into behaviour or performance.

This study addresses both gaps by modelling employee innovation as the outcome, talent management effectiveness as the mediating mechanism and top management support as a measured boundary condition. Grounded in the resource-based view (Barney, 1991) and dynamic capabilities theory (Teece et al., 1997), it treats analytics as the sensing capability, talent management as the seizing capability and innovation as the transforming outcome. The question is therefore not whether analytics matters in the abstract, but how, and under what leadership conditions, it matters for innovation.

The study makes three contributions. First, it provides empirical support for talent management as the mediating mechanism between analytics and innovation, a chain proposed but not confirmed in prior work (Noor et al., 2025). Second, it integrates four theoretical perspectives into a single explanatory model. Third, it tests top management support as a boundary condition and shows that its role is additive rather than amplifying. The remainder of the paper develops the hypotheses, describes the method, reports the results and discusses their implications.

2. Theoretical Background and Hypotheses

2.1 Theoretical foundations

The resource-based view holds that competitive advantage stems from resources that are valuable, rare, inimitable and non-substitutable (Barney, 1991). HR analytics capability can be viewed as a meta-resource: it raises the strategic value of human capital by turning raw workforce records into insight that competitors find hard to imitate (Noor et al., 2025). Dynamic capabilities theory explains how firms renew such advantage by sensing opportunities, seizing them through resource mobilisation and transforming themselves to sustain the gain (Teece et al., 1997). In the present model, analytics is the sensing mechanism that gathers knowledge on skills, attrition and innovation potential; talent management is the seizing mechanism that converts this knowledge into practice; and employee innovation is the transforming outcome.

Two further frameworks refine the mechanism and its boundary condition. The ability–motivation–opportunity (AMO) framework proposes that performance arises when people have the ability and motivation to act and the opportunity to do so (Appelbaum et al., 2000). Because talent management is the system that supplies these three conditions, it should be the proximal driver of innovative behaviour. The technology–organisation–environment (TOE) framework adds that the value of a technological capability depends on organisational context, of which top management support is a defining element (Tornatzky & Fleischer, 1990).

2.2 HR analytics capabilities and employee innovation

HR analytics capability is the organisation's ability to conduct descriptive, visual and statistical analyses of HR and performance data (Marler & Boudreau, 2017). It rests on tangible resources (data and technology), human skills (analytical competencies) and intangible assets (a data-driven

culture) (Arora & Mittal, 2024). Although the field has moved from descriptive towards predictive and prescriptive analytics (Fitz-Enz & Mattox, 2014; Margherita, 2021), many organisations remain at the descriptive stage, largely for lack of analytical expertise (Cayrat & Boxall, 2022; Fernandez & Gallardo-Gallardo, 2021; Vargas et al., 2018).

Employee innovation is the extent to which individuals generate, develop and implement new ideas that strengthen the organisation's competitiveness (Anderson et al., 2004; Maqableh & Al-Shawabkeh, 2025). In a survey of 418 Indian HR professionals, Arora and Mittal (2024) found that analytics capabilities explained substantial variance in performance (R^2 = .683), with innovative capability the strongest predictor and a mediator of the analytics–performance link. Analytics can also support innovation directly by making decision making visibly evidence-based and by encouraging knowledge sharing, which legitimises the search for new ideas.

H1: HR analytics capabilities have a positive effect on employee innovation.

2.3 HR analytics capabilities and talent management effectiveness

Talent management is the strategic process of attracting, developing and retaining high-potential individuals in line with organisational objectives (Maqableh & Al-Shawabkeh, 2025). It spans acquisition, performance management, development, succession planning and retention (Alzyadat et al., 2024; Collings & Mellahi, 2009). Analytics supplies data on performance, turnover, development and succession, which makes talent decisions more precise by predicting attrition, guiding development and identifying high performers (Marler & Boudreau, 2017). Muchowe et al. (2025) likewise found that the productivity gains from analytics were greatest when it was combined with high-performance work practices.

H2: HR analytics capabilities have a positive effect on talent management effectiveness.

2.4 Talent management effectiveness and employee innovation

From an AMO perspective, effective talent practices build the skills, motivation and opportunity that innovation requires. Alzyadat et al. (2024) showed that acquisition, training, development and retention practices improve employee skills and commitment, which in turn drive human-capital performance. Innovation is also more likely when it is treated as part of the ordinary job and when leaders cultivate a supportive climate (Maqableh & Al-Shawabkeh, 2025).

H3: Talent management effectiveness has a positive effect on employee innovation.

2.5 The mediating role of talent management effectiveness

Analytics can tell an organisation something about its people, but talent management installs the practices that make creative behaviour more likely. In dynamic-capabilities terms, a sensing resource creates value only when seizing mechanisms translate it into action (Teece et al., 1997). Noor et al. (2025) proposed this chain but did not find strong support for it, which underlines how context-dependent the process is and why it needs direct testing.

H4: Talent management effectiveness mediates the relationship between HR analytics capabilities and employee innovation.

2.6 The moderating role of top management support

Top management support refers to senior leaders' commitment, encouragement, resource provision and strategic participation in implementing analytics and fostering innovation. Analytical insight alone does not translate into better practice; it requires the resources, priority and legitimacy that leaders provide (Arora & Mittal, 2024). Consistent with the TOE framework (Tornatzky & Fleischer, 1990), the same analytical insight should yield more effective talent decisions when senior leaders actively champion the analytics agenda, and may stall where such backing is weak (Noor et al., 2025).

H5: Top management support moderates the relationship between HR analytics capabilities and talent management effectiveness, such that the relationship is stronger when top management support is higher.

Figure 1 summarises the research model.

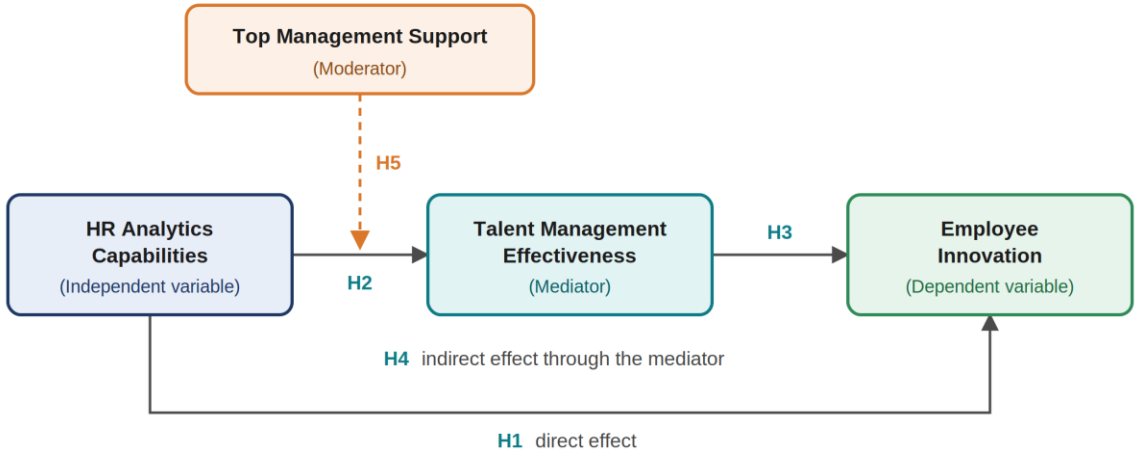


Figure 1. Conceptual model and hypotheses

Note. H1 = direct effect of HR analytics capabilities on employee innovation; H2 and H3 = the two paths that form the indirect effect tested as mediation (H4); H5 = moderation of the HR analytics → talent management path by top management support.

3. Method

3.1 Design, sample and procedure

A quantitative, cross-sectional survey design was adopted because the study tests directional hypotheses and estimates direct, indirect and conditional effects among well-defined constructs (Hair et al., 2022). The target population comprised HR professionals, line managers and employees of mid- to large-sized organisations in manufacturing, banking and financial services, telecommunications, healthcare and technology, sectors chosen to span a range of analytics maturity. Respondents were reached through professional networks using convenience sampling, supplemented by referral (snowball) sampling, consistent with prior studies in this domain (Arora & Mittal, 2024; Etikan et al., 2016; Vargas et al., 2018).

Data were collected through a self-administered online questionnaire with unique links to prevent duplicate submissions. An a priori power analysis in G*Power 3.1 (Faul et al., 2007) indicated that 92 cases were needed to detect a medium effect (f^2 = 0.15) with power of .80; the 112 usable responses obtained exceed this threshold. Most respondents were male (66.1%), married (73.2%), aged 26–40 years (51.8%) and employed full-time (85.7%). Nearly three-quarters held supervisory or managerial positions (73.2%), which suits a survey on organisation-level analytics and talent practices. The largest tenure groups were up to five years (33.9%) and 11–20 years (30.4%).

Participation was voluntary and based on informed online consent. Respondents received an information sheet explaining the study's purpose and their right to withdraw. No identifying information beyond voluntary demographics was collected, data were stored on a password-protected server, and results are reported only in aggregate.

3.2 Measures

All constructs were measured with validated multi-item scales on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (Dawes, 2008).

HR analytics capabilities were measured with the 12-item scale of Su et al. (2022), as validated by Arora and Mittal (2024), covering tangible resources, human analytical skills and data-driven culture (e.g., "We base our decisions on data rather than on instinct"; α = .902).

Talent management effectiveness was measured with 26 items adapted from Noor et al. (2025) and the wider talent literature (Collings & Mellahi, 2009; Subramaniam et al., 2018), covering acquisition, development, retention, performance management, recognition and succession planning (e.g., "Talents have clear career paths in my organization"; α = .969).

Employee innovation was measured with items from Ilmudeen (2022) as used by Arora and Mittal (2024), covering idea generation, application of novel ideas and creative identity (e.g., "I often think about being creative"; α = .834).

Top management support was measured with five items drawn from McCartney and Fu (2022) and Noor et al. (2025), capturing senior executives' endorsement, resource commitment and validation of analytics-informed HR initiatives (e.g., "Top management is supportive of our efforts to improve the HR analytics capabilities"; α = .809).

Control variables. Gender, marital status, age, work status, job position and organisational tenure were not significantly related to the study variables ($p > .05$) and were therefore not retained as controls.

3.3 Analytical procedure

Analyses were conducted in IBM SPSS with the PROCESS macro (v5.0; Hayes, 2018). Reliability was assessed with Cronbach's alpha, and the constructs were summarised with means, standard deviations and Pearson correlations. H1–H3 were tested with ordinary least squares regression. H4 was tested by estimating the indirect effect of analytics on innovation through talent management with bias-corrected bootstrapping (5,000 resamples; Preacher & Hayes, 2008). Mediation was inferred when the confidence interval excluded zero, and classified as partial or full according to whether the direct effect remained significant. H5 was tested with hierarchical moderated regression: the mean-centred predictors were entered in Step 1 and the analytics × support interaction in Step 2 (Hayes, 2018).

4. Results

4.1 Descriptive statistics and correlations

Mean scores ranged from 3.50 (HR analytics capabilities) to 3.69 (employee innovation), above the scale midpoint, suggesting that respondents viewed their organisations as moderately rather than highly proficient in all four areas. Standard deviations (0.76–0.95) indicate adequate dispersion. All correlations were positive and significant ($p < .001$), ranging from .78 to .90 (Table 1). The strongest associations were between talent management effectiveness and top management support ($r = .90$) and between talent management effectiveness and employee innovation ($r = .89$). These magnitudes support the hypothesised links but also indicate substantial shared variance, which is addressed in the limitations.

Table 1. Means, standard deviations, reliabilities and correlations (N = 112)

Variable	M	SD	1	2	3	4
1. HR analytics capabilities	3.50	0.79	(.90)			
2. Talent management effectiveness	3.67	0.85	.87***	(.97)		
3. Employee innovation	3.69	0.76	.83***	.89***	(.83)	
4. Top management support	3.66	0.95	.78***	.90***	.83***	(.81)

Note. Cronbach's alpha on the diagonal in parentheses. *** p < .001.

4.2 Direct effects (H1–H3)

HR analytics capabilities significantly predicted employee innovation (β = .84, $p < .001$, $R^2 = .700$) and talent management effectiveness (β = .86, $p < .001$, $R^2 = .747$). Talent management effectiveness, in turn, significantly predicted employee innovation (β = .89, $p < .001$, $R^2 = .794$) and was the strongest

single predictor in the model. H1, H2 and H3 were therefore supported (Table 2).

4.3 Mediation analysis (H4)

The total effect of HR analytics capabilities on employee innovation was significant (b = 0.88, p < .001). With talent management effectiveness included as a mediator, the indirect effect was significant (effect = 0.60, Boot SE = 0.09, 95% bias-corrected CI [0.43, 0.77]). The direct effect remained significant but smaller (b = 0.27, p = .005), indicating partial mediation. The indirect path accounts for about 68% of the total effect, suggesting that analytics reaches innovation mainly by strengthening how organisations acquire, develop and retain people. H4 was supported.

4.4 Moderation analysis (H5)

In Step 1, HR analytics capabilities (b = 0.65, 95% CI [0.22, 1.07]) and top management support (b = 0.65, 95% CI [0.27, 1.03]) jointly explained 87.8% of the variance in talent management effectiveness, and both were significant. In Step 2, the interaction term was not significant (b = −0.05, SE = 0.05, 95% CI [−0.16, 0.06]) and added negligible explained variance (ΔR^2 = .002, F = 0.77, p = .384). H5 was therefore not supported: the level of top management support did not change the strength of the analytics–talent management relationship (Table 3). Overall, four of the five hypotheses were supported.

Table 2. Direct and indirect effects

Hypothesis	Path	Estimate	SE	95% CI	Decision
H1	HR analytics → Employee innovation	β = .84***	0.06	[0.76, 0.99]	Supported
H2	HR analytics → Talent management	β = .86***	0.06	[0.85, 1.08]	Supported
H3	Talent management → Employee innovation	β = .89***	0.04	[0.75, 0.92]	Supported
H4	HR analytics → Talent management → Employee innovation (indirect)	0.60	0.09	[0.43, 0.77]	Supported (partial mediation)

Note. β = standardised coefficient; SE and CI refer to the unstandardised coefficient. The indirect effect is unstandardised, with a bias-corrected bootstrap CI based on 5,000 resamples. *** p < .001.

Table 3. Moderated regression (dependent variable: talent management effectiveness)

Predictor	b	SE	95% CI	R^2 (ΔR^2)
Step 1				**.878**
HR analytics capabilities	0.65	0.21	[0.22, 1.07]	
Top management support	0.65	0.19	[0.27, 1.03]	
Step 2				**.880 (.002)**
HR analytics × Top management support	−0.05	0.05	[−0.16, 0.06]	

Note. Predictors were mean-centred. Confidence intervals that exclude zero indicate significance.

5. Discussion

5.1 Interpretation of findings

HR analytics capabilities had a strong positive effect on employee innovation, explaining 70% of its variance (H1). This is consistent with Arora and Mittal (2024), who identified innovative capability as the key conduit between analytics and performance, and with the resource-based view that analytics generates firm-specific insight about people. It contrasts with Noor et al. (2025), who found no such effect, suggesting that the direct link emerges where the supporting conditions are in place. Analytics makes evidence-based decision making visible and encourages information sharing, which raises the perceived legitimacy of proposing new ideas.

Analytics also predicted talent management effectiveness (H2), supporting the argument of Marler and Boudreau (2017) that analytics sharpens talent decisions by predicting attrition, guiding development and identifying high performers. In dynamic-capabilities terms, this is the link between sensing and seizing. Talent management effectiveness, in turn, was the strongest predictor of innovation, explaining about 79% of its variance (H3). This fits the AMO framework (Appelbaum et al., 2000) and extends Alzyadat et al. (2024): talent practices that build skills, motivate through recognition and fair reward, and create opportunity through career paths and job design are the practices most closely tied to innovative behaviour.

The mediation result (H4) is arguably the study's most important finding. Talent management carried about two-thirds of the effect of analytics on innovation, recasting analytics less as a tool that acts directly on employees and more as one that works by strengthening the talent system. Noor et al. (2025) proposed but could not confirm this chain; the present results support it. The partial pattern is theoretically plausible, since analytics may also reach innovation through more direct routes such as an evidence-based climate and information exchange.

Contrary to H5, top management support did not moderate the analytics–talent management relationship. Two explanations are likely. First, support acted as a strong main effect rather than a moderator, so its influence appears additive rather than conditional. Second, as in Maqableh and Al-Shawabkeh (2025), restricted independent variance may have limited the interaction test: respondents who reported strong analytics also reported strong leadership support (r = .78). The most defensible reading is that analytics predicted talent management effectiveness regardless of perceived leadership support, and that leadership mattered as a direct contributor rather than an amplifier.

5.2 Theoretical implications

The study makes three theoretical contributions. First, it extends the resource-based view by showing that the value of HR analytics, as a meta-resource, is realised mainly through a complementary HR system rather than in isolation. Second, it offers empirical support for the dynamic-capabilities sequence in the HR domain, with analytics as sensing, talent management as seizing and innovation as transforming. Third, it refines the TOE framework by showing that leadership support functioned as an additive readiness factor rather than a conditional amplifier, at least in a context where support was generally present. Together with the AMO framework, these perspectives explain why the talent system, rather than analytics per se, is the proximal driver of innovation.

5.3 Practical implications

Three implications follow for practice. First, organisations seeking innovation should treat analytics investment as a strategic talent and innovation initiative rather than a technology project, and develop all three dimensions of capability: data infrastructure, analytical skills and a data-driven culture (Arora & Mittal, 2024). Second, analytics should be embedded in talent management rather than run as a parallel system, so that its insights feed directly into acquisition targeting, development priorities, retention-risk scoring and succession decisions. Strengthening the talent system is the highest-leverage move identified here. Third, leaders should visibly resource and legitimise both analytics and talent practices, since support was a strong direct predictor of talent management effectiveness. However, HR practitioners need not wait for

perfect leadership buy-in before using analytics, because its effect held across levels of support.

5.4 Limitations and future research

Several limitations should be noted. First, the cross-sectional design precludes causal claims; longitudinal or time-lagged designs would allow causal ordering to be tested. Second, reliance on single-source self-reports raises the risk of common method bias (Podsakoff et al., 2003); multi-source data would mitigate this. Third, the very high inter-construct correlations (up to .90) raise concerns about discriminant validity, which future studies should assess formally with confirmatory factor analysis and structural equation modelling. Fourth, the convenience sample of 112 respondents limits generalisability, so larger and more diverse samples are needed. Finally, future research could examine top management support as an antecedent or mediator rather than a moderator, and explore additional mechanisms such as data-driven climate and knowledge sharing.

6. Conclusion

This study shows that HR analytics capabilities foster employee innovation, mainly by strengthening talent management effectiveness. About two-thirds of the effect of analytics on innovation flows through the talent system, while a smaller direct effect remains. Top management support raised talent management effectiveness directly but did not amplify the effect of analytics. For organisations, the innovation return on analytics therefore depends less on the technology itself than on how closely its insights are built into the way people are acquired, developed and retained.

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