

Activating Digital Talent Ecosystems for Operational Innovation: The Roles of Employee Agility and Digital Leadership

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ABSTRACT

The rapid digital transformation of public administration requires organisations to recalibrate strategic talent management to drive operational innovation. Grounded in Socio-Technical Systems Theory and the Dynamic Capabilities View, this study investigates how digitalised talent management practices influence operational innovation through employee agility and examines whether digital leadership moderates the relationships between digital talent management practices and employee agility. Utilising a quantitative cross-sectional design, primary data from 412 UAE federal government employees were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The structural results indicate that digital talent identification ($\beta = 0.231$, $p < 0.001$), continuous reskilling ($\beta = 0.284$, $p < 0.001$), and AI-augmented engagement ($\beta = 0.215$, $p < 0.001$) significantly drive employee agility, which subsequently exerts a strong direct effect on operational innovation ($\beta = 0.462$, $p < 0.001$). Together, the predictors explain 61.4% of the variance in employee agility ($R^2 = 0.614$) and 58.7% of the variance in operational innovation ($R^2 = 0.587$). Furthermore, digital leadership significantly and positively moderated the relationships between digital talent management practices and employee agility. These findings provide public sector leaders with empirical insights into the positive associations between digital HR practices, employee agility, and reported operational innovation within public administration.

Keywords: Digital Talent Management, Employee Agility, Operational Innovation, Digital Leadership, Public Sector Administration

INTRODUCTION

In the rapidly evolving landscape of global public administration, the digital era has emerged as a defining force, fundamentally reshaping the structure of work and the strategic mandate of talent management (Kraus et al., 2021; Stone et al., 2015). Organisations today navigate an environment marked by relentless technological disruption, where data-driven decision-making and extreme agility in workforce planning define operational survival and institutional success (Cascio & Montealegre, 2016). Over the past decade, human resource management (HRM) has evolved from a heavily administrative, compliance-driven function into a highly strategic institutional pillar that significantly influences organisational performance and sustained competitiveness (Budhwar et al., 2022; Wright & McMahan, 2011). For modern governance frameworks, particularly within the United Arab Emirates (UAE) federal government, which is pursuing the 'We the UAE 2031' vision, integrating digital technologies such as artificial intelligence (AI), machine learning, and predictive analytics into HR management processes plays an increasingly important role in maintaining institutional efficacy (Al-Ali et al., 2017). The emergence of algorithmic governance and advanced digital platforms has transformed HRM globally, prompting public sector organisations to increasingly rely on digital recruitment platforms, electronic performance systems, and data-driven HR analytics to overcome the inefficiencies of legacy bureaucratic systems (Marler & Fisher, 2013; Tambe et

al., 2019).

The transition to digitally based work systems requires employees to possess not only adequate digital technical skills but also the profound cognitive agility to continuously adapt to an ever-changing technological landscape (Boudreau & Cascio, 2017). Legacy public sector administration has historically relied on standardised personnel management practices, often constrained by subjective appraisals and siloed structures (Claus, 2019). In modern digital economies, these traditional frameworks can create administrative friction, hindering workforce adaptability (Boudreau & Cascio, 2017). As public governance shifts toward algorithmic frameworks (Tambe et al., 2019), organisations require ecosystems that integrate technological infrastructure with human adaptability to sustain operational performance. In this study, operational innovation refers to employees' perceptions that their work unit regularly develops and implements new or improved methods, processes, or approaches to enhance service delivery and operational effectiveness. According to the World Economic Forum (2023), organisations face a severe risk of losing their competitive edge if they fail to adopt agile learning ecosystems and predictive talent analytics. In response to these pressing macro-environmental challenges, leading entities are implementing predictive analytics in talent acquisition, continuous micro-learning ecosystems, and AI-powered performance mapping (Malik et al., 2022). By automating highly repetitive mental tasks and administrative activities, AI technologies augment rather than replace human resource functions, forging a socio-technical symbiosis that supports complex strategic planning and elevates the employee experience (Kellogg et al., 2020; Varma et al., 2023).

Despite the growing consensus on the necessity of digitalising human resources, a critical empirical gap remains in understanding the precise psychological and behavioural mechanisms by which these digital practices translate into organisational innovation (Meijerink et al., 2021). Previous studies have frequently focused on the procedural or financial aspects of digital HR implementation without adequately exploring the subsequent impacts on individual agility or operational output (Tams et al., 2020). Furthermore, while digital tools provide the necessary technological infrastructure, capable digital leadership is theoretically required to foster a psychological environment in which digital talent management can thrive (Cortellazzo et al., 2019). Addressing these lacunae, this research bridges existing empirical gaps by investigating a complex moderated-mediation structural model. The study evaluates how specific digitalised HR practices (identification, reskilling, and engagement) foster individual cognitive agility and operational innovation, while simultaneously testing the pivotal boundary influence of digital leadership within the UAE federal government context.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The study primarily draws on the Dynamic Capabilities View and the Socio-Technical Systems Theory. DCV provides the overarching explanation for how organisations develop and reconfigure capabilities in response to technological change, while STS theory explains how technological infrastructure and employee-level behavioural adaptation jointly shape organisational outcomes. Employee agility is conceptualised as a micro-level mechanism by which organisational digital practices translate into operational innovation. Digital leadership is subsequently positioned as a contextual leadership condition that strengthens employees' ability to convert digital talent practices into adaptive behaviour. The DCV framework explains how organisations reconfigure internal competencies to adapt to volatile environments, providing the foundation for viewing employee agility as a micro-foundational dynamic capability. STS Theory posits that organisational optimisation requires the joint optimisation of technological subsystems (AI platforms) and social subsystems (employee cognitive adaptability) (Davis, 2018). Finally, Upper Echelons Theory explains how executive leadership mindsets, technological fluencies, and strategic orientations shape the operational environment for innovation (Hambrick, 2007).

Digital talent identification represents a paradigm shift from subjective human resource evaluation to algorithmic, data-driven talent decisions. It utilises predictive analytics, natural language processing, and machine learning to streamline candidate sourcing, identify latent skill gaps, and execute highly accurate performance mapping (Bresciani et al., 2021; Daugherty & Wilson, 2018). Algorithmic recruitment and

performance systems, when effectively evaluated for procedural justice, transparency, and bias mitigation, function as a vital trust-building mechanism for employees, fundamentally enhancing their perceived organisational support and psychological safety (Chalubínek et al., 2023; Garcia-Arroyo & Osca, 2019). When employees perceive that their unique competencies are accurately mapped by impartial digital algorithms rather than subjective managerial bias, their psychological willingness to embrace cross-functional, agile behaviours substantially increases, liberating them to focus on capability expansion rather than political posturing. While scholars caution that automated evaluation can induce perceptions of surveillance if systems lack transparency (Kellogg et al., 2020), digital talent mapping primarily acts as a supportive diagnostic tool when paired with open governance. Therefore, Hypothesis 1 posits that digital talent identification is significantly and positively related to employee agility.

Organisations that consistently facilitate continuous training, share institutional knowledge, and create an optimal learning environment provide employees with vital opportunities to develop their digital competencies in real time (Aguinis & Kraiger, 2009). Proactive upskilling and reskilling initiatives equip employees with the competencies needed to meet the evolving, highly volatile demands of the digital workforce (Bughin et al., 2018). Given that technological shifts constantly threaten skill obsolescence, structured training programmes that leverage AI's capacity to offer personalised, on-demand micro-learning and development opportunities are critical drivers for maintaining human resource capacity (Lund et al., 2019; Noe et al., 2014). Continuous reskilling support signals the organisation's long-term commitment to the employee's employability, which, in turn, fosters proactive adaptability and a willingness to step outside traditional role boundaries (Ellström, 2001; Salas et al., 2012). Consequently, Hypothesis 2 posits that continuous reskilling support is significantly and positively related to employee agility.

Furthermore, AI-enabled strategic decision-making improves organisational agility and performance by facilitating adaptive management approaches and augmenting the employee experience (Raisch & Krakowski, 2021). The rapid integration of AI into HRM practices has enabled organisations to automate repetitive administrative tasks, often termed "bureaucratic friction"—thus freeing human resource professionals and general employees to focus their cognitive bandwidth on more strategic, value-adding initiatives (Budhwar et al., 2022). AI-augmented engagement seeks to redefine professional boundaries by combining human intuition, empathy, and socio-emotional understanding with the precise analytical and predictive capabilities of AI (Malik et al., 2020; Varma et al., 2023). By utilising intelligent chatbots for immediate HR query resolution and sentiment analysis tools to proactively identify burnout, organisations can maintain high levels of psychological availability among staff. Thus, Hypothesis 3 posits that AI-augmented engagement is significantly and positively related to employee agility.

Employee agility, characterised by rapid cognitive adaptability, proactive skill acquisition, and a high tolerance for ambiguity, serves as the primary mechanism for creating technological value (Dyer & Shafer, 1999; Muduli, 2015). Within the micro-foundations' perspective of dynamic capabilities, employee agility is conceptualised as an individual-level behavioural mechanism through which organisational practices can contribute to adaptive organisational outcomes. The present study does not treat individual agility as equivalent to an organisational dynamic capability; rather, it examines employee agility as a proximal behavioural mechanism that links digital talent practices to perceived operational innovation. Because operational innovation is an urgent imperative for maintaining relevance and generating public value in an evolving public sector (Anderson et al., 2014; Nambisan et al., 2019), agile employees are fundamental drivers of process reengineering and new service delivery methods. They possess the cognitive flexibility to creatively apply new digital tools to legacy public sector problems (Shalley et al., 2004). Therefore, Hypothesis 4 posits that employee agility has a significant positive effect on operational innovation performance. Extending this logic, digital infrastructure alone is insufficient to generate operational innovation; it must first alter individual employee behaviour. Consequently, employee agility is theorised to function as the essential mediating mechanism that converts digital HR inputs into public-sector innovation outcomes. Thus, we propose:

Hypothesis 5a (H5a): Employee agility significantly mediates the relationship between digital talent identification and operational innovation.

Hypothesis 5b (H5b): Employee agility significantly mediates the relationship between continuous reskilling support and operational innovation.

Hypothesis 5c (H5c): Employee agility significantly mediates the relationship between AI-augmented engagement and operational innovation.

Finally, the challenge of resistance to technological change must be overcome through effective change management and unwavering leadership support to shape a culture of continuous digital innovation. Leadership paradigms must undergo significant transformations to address digital inclusion, technological disruption, and the ethical considerations inherent in algorithmic management (Cortellazzo et al., 2019; Sovacool et al., 2018). Digital leadership transcends standard transformational leadership; it requires profound digital literacy, the ability to architect digital visions, and the emotional intelligence to guide employees through the anxieties of automation (Avolio et al., 2014; Bennis, 2013). Vital to cultivating a robust organisational culture are leaders who actively champion digital talent systems, thereby creating a perimeter of psychological safety for iterative experimentation (Kane et al., 2019). Consequently, Hypotheses 6a, 6b, and 6c propose that digital leadership positively moderates the relationships between digital talent identification (H6a), continuous reskilling support (H6b), AI-augmented engagement (H6c) and employee agility, such that these positive relationships are stronger when digital leadership is high.

CONCEPTUAL FRAMEWORK

The structural model tested in this study examines a complex moderated-mediation pathway as shown in Figure 1. The three independent variables (Digital Talent Identification, Continuous Reskilling Support, and AI-Augmented Engagement) are posited to directly predict the mediating variable (Employee Agility). Employee Agility subsequently predicts the ultimate endogenous dependent variable (Operational Innovation). Digital Leadership acts as a crucial boundary-spanning moderating variable, specifically theorised to amplify the direct relationships between the three digital talent management practices and Employee Agility.

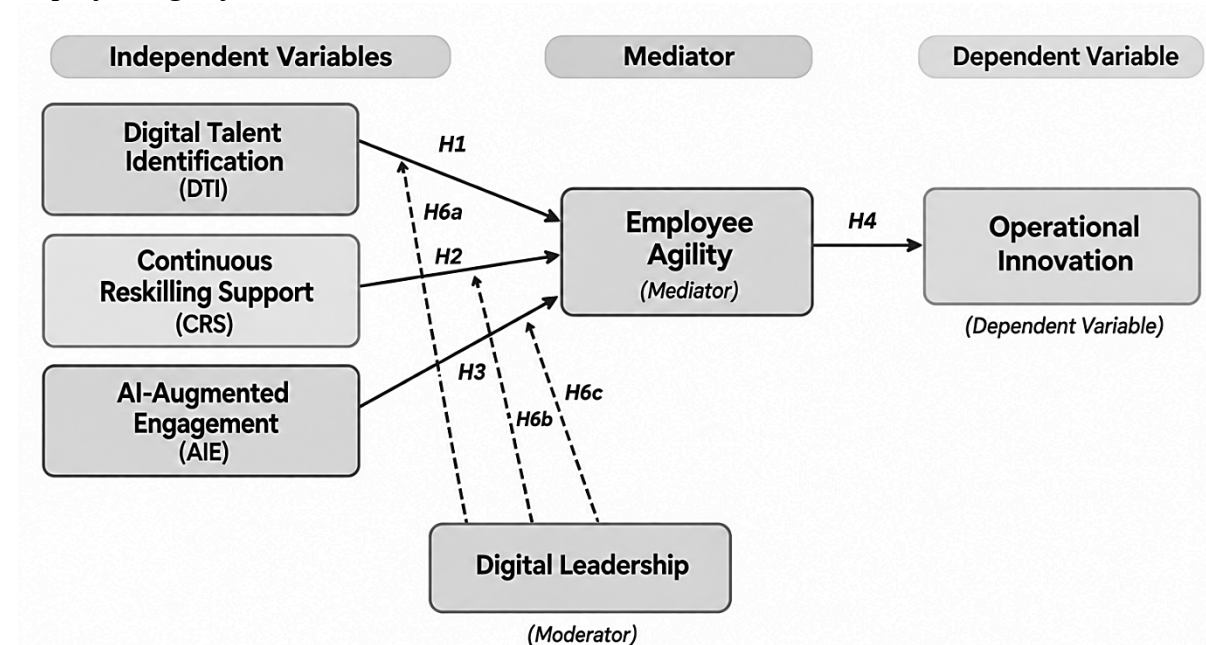


Figure 1: Conceptual Model of Digitalised Talent Management Ecosystems, Employee Agility, Digital Leadership, and Operational Innovation

Note: H5a, H5b, and H5c represent the specific indirect (mediation) effects of DTI, CRS, and AIE on Operational Innovation via Employee Agility.

METHODOLOGY

To rigorously test the proposed hypotheses, this study adopted a quantitative, explanatory cross-sectional

research design. Data analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) to evaluate the predictive effects of the constructs and to formally test the complex mediating and moderating variables. PLS-SEM was selected as the optimal analytical technique due to its superior capability in handling complex moderated-mediation frameworks, its lack of strict assumptions regarding multivariate normality, and its focus on maximising the explained variance of the endogenous constructs, consistent with the methodological guidelines established by Hair et al. (2019). Sample size adequacy was confirmed a priori using G*Power software, which indicated that a minimum sample of 153 was required to detect a medium effect size ($f^2 = 0.15$) with a statistical power of 0.95 at an alpha level of 0.05 (Faul et al., 2009).

A stratified random sampling technique was utilised to collect primary data from 412 full-time civil servants operating across multiple UAE federal ministries, heavily exceeding the G*Power minimum requirements and ensuring robust statistical power. Table 1 presents the detailed demographic profile of the 412 respondents, including gender, age group, educational attainment, organisational tenure, job level, and employing ministry/agency. All measurement scales were adapted from validated instruments in the existing literature, as shown in Table 1. Digital Talent Identification was measured using 4 items adapted from Bresciani et al. (2021); Continuous Reskilling Support was operationalized using 5 items from Noe et al. (2014); AI-Augmented Engagement was measured using 4 items adapted from Malik et al. (2020); Employee Agility was evaluated with 5 items adapted from Muduli (2015); Operational Innovation was measured using 5 items from Anderson et al. (2014); and Digital Leadership was assessed using 5 items adapted from Kane et al. (2019).

Table 1: Demographic Profile of Survey Respondents (N = 412)

Demographic Category	Sub-Category	Frequency (n)	Percentage (%)
Gender	Male	218	52.90%
	Female	194	47.10%
Age Group	Under 30 years	64	15.50%
	30–39 years	182	44.20%
	40–49 years	126	30.60%
	50 years and above	40	9.70%
Educational Attainment	Bachelor’s Degree	254	61.70%
	Master’s Degree	128	31.10%
	Doctorate / PhD	30	7.20%
Organizational Tenure	Less than 3 years	52	12.60%
	3–7 years	165	40.00%
	8–12 years	123	29.90%
	More than 12 years	72	17.50%
Job Level	Non-Managerial / Technical Specialist	268	65.00%
	Middle Management / Team Lead	104	25.20%
	Executive / Senior Management	40	9.80%
Employing Ministry / Entity	Ministry of Human Resources & Emiratisation	98	23.80%
	Ministry of Finance	84	20.40%
	Ministry of Economy	76	18.40%
	Ministry of Cabinet Affairs	62	15.00%
	Other Participating Federal Entities	92	22.40%
Total		412	100.00%

All items were evaluated on a 5-point Likert scale ranging from 1 ('Strongly Disagree') to 5 ('Strongly Agree'). The English instrument was independently translated into Arabic by a bilingual translator familiar with organisational research. A second bilingual translator independently back-translated the Arabic version into English without access to the original instrument. Discrepancies were reviewed by a bilingual research panel and resolved through consensus. The revised Arabic instrument was subsequently pilot-tested with respondents who matched the target population. Because all predictor, mediator, moderator, and criterion variables were captured from the same respondents simultaneously, stringent procedural remedies were implemented to mitigate common method bias (CMB). These included the psychological separation of constructs as shown in Table 2, variation in anchor wording, and assurances of absolute anonymity for respondents. Statistically, a full collinearity assessment was conducted post hoc; all inner variance inflation factor (VIF) values were below the conservative 3.3 threshold established by Kock (2015), confirming that common method bias did not contaminate the dataset, in line with Podsakoff et al. (2003, 2012).

Table 2: Operationalisation and Sources of Measurement Constructs

Construct	No. of Items	Sample Measurement Item	Source Scale
Digital Talent Identification (DTI)	4	"Our agency uses objective digital analytics to identify latent skill gaps."	Adapted from Bresciani et al. (2021)
Continuous Reskilling (CRS)	5	"My department provides on-demand micro-learning pathways for digital skills."	Adapted from Noe et al. (2014)
AI-Augmented Engagement (AIE)	4	"Automated HR systems reduce routine tasks, allowing focus on core duties."	Adapted from Malik et al. (2020)
Employee Agility (EA)	5	"I adapt quickly when introduced to new digital tools and processes."	Adapted from Muduli (2015)
Operational Innovation (OI)	5	"Our team regularly implements new methods to enhance service delivery."	Adapted from Anderson et al. (2014)
Digital Leadership (DL)	5	"My supervisor actively promotes digital transformation and experimentation."	Adapted from Kane et al. (2019)

While procedural remedies (e.g., psychological separation of items and respondent anonymity) and statistical checks (inner VIF values below 3.3) indicate that common method variance is not a pervasive threat to the data, reliance on single-source, cross-sectional self-reports remains an inherent methodological limitation. Future investigations should incorporate multi-source or objective operational metrics to further validate these findings.

RESULTS

The initial phase of the PLS-SEM analysis involved an exhaustive assessment of the measurement model to establish internal consistency, indicator reliability, and convergent validity. As detailed in Table 3, all constructs exhibited Cronbach's alpha and Composite Reliability (CR) values substantially exceeding the highly acceptable 0.70 benchmark, indicating exceptional internal consistency. Additionally, convergent validity was firmly established, as the Average Variance Extracted (AVE) for each latent variable exceeded the stringent 0.50 threshold, indicating that the constructs explained the majority of the variance in their respective indicators.

Table 3: Measurement Model Assessment

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Digital Talent Identification (DTI)	0.884	0.912	0.654
Continuous Reskilling Support	0.912	0.931	0.718

(CRS)			
AI-Augmented Engagement (AIE)	0.895	0.924	0.687
Employee Agility (EA)	0.924	0.942	0.741
Operational Innovation (OI)	0.901	0.928	0.699
Digital Leadership (DL)	0.932	0.945	0.772

Following confirmation of convergent validity, discriminant validity was rigorously evaluated using the advanced Heterotrait-Monotrait (HTMT) ratio criterion advocated by Henseler et al. (2015), which offers superior sensitivity for detecting discriminant anomalies compared to traditional criteria. As presented in Table 4, all derived HTMT values fell comfortably below the conservative 0.85 threshold. The highest observed correlation ratio was between continuous reskilling support and employee agility, at 0.785, which is theoretically expected yet statistically distinct enough to confirm that each construct measures a unique organisational phenomenon without detrimental conceptual overlap.

Table 4: Discriminant Validity (HTMT Ratio)

Construct	DTI	CRS	AIE	EA	OI	DL
DTI	-					
CRS	0.642	-				
AIE	0.591	0.612	-			
EA	0.714	0.785	0.688	-		
OI	0.633	0.721	0.655	0.812	-	
DL	0.554	0.601	0.582	0.677	0.611	-

Collinearity diagnostics were performed prior to structural path estimations. The inner Variance Inflation Factor (VIF) values ranged from 1.34 to 2.71, eliminating concerns about multicollinearity and ensuring the stability of the path estimates. The structural model analysis, executed with a 5,000-subsample bootstrapping procedure, provided empirical support for the direct and mediating hypotheses for the direct and mediating hypotheses, as outlined in Table 5.

Table 5: Structural Model and Hypothesis Testing (Direct Effects)

Hypothesis	Path	β	t	p	f ²	Decision
H1	DTI → EA	0.231	4.882	<0.001	0.082(small)	Supported
H2	CRS → EA	0.284	5.914	<0.001	0.124(small)	Supported
H3	AIE → EA	0.215	4.633	<0.001	0.071(small)	Supported
H4	EA → OI	0.462	9.125	<0.001	0.271(medium)	Supported

The moderation analysis introduced formal interaction terms to ascertain the boundary influence of digital leadership on the agility-generating capacity of HR ecosystems. As detailed in Table 5, digital leadership significantly and positively moderated the relationships across all three digital talent practices. Employee agility significantly predicted operational innovation ($\beta = 0.462$, $t = 9.125$, $p < 0.001$).

The structural model exhibited strong overall explanatory power, accounting for 61.4% of the variance in employee agility ($R^2 = 0.614$) and 58.7% of the variance in operational innovation ($R^2 = 0.587$), fully supporting the set of structural pathways specified in Figure 1. Furthermore, predictive relevance was established using the blindfolding procedure; the resulting Stone-Geisser Q^2 values for Employee Agility ($Q^2 = 0.448$) and Operational Innovation ($Q^2 = 0.402$) were substantially above zero, confirming the predictive validity of the structural framework.

Table 6: Moderation Analysis Results

Hypothesis	Interaction Term	Beta (β)	t-value	p-value	Decision
H6a	DTI $\times$ DL $\rightarrow$ Employee Agility	0.112	3.014	0.003	Supported
H6b	CRS $\times$ DL $\rightarrow$ Employee Agility	0.145	3.988	< 0.001	Supported
H6c	AIE $\times$ DL $\rightarrow$ Employee Agility	0.108	2.841	0.005	Supported

As shown in Table 6, Digital leadership positively moderated the relationship between digital talent identification and employee agility ($\beta = 0.112$, $t = 3.014$, $p = 0.003$, 95% CI [0.039, 0.185]). Similar positive interaction effects were observed for continuous reskilling support ($\beta = 0.145$, $t = 3.988$, $p < 0.001$, 95% CI [0.074, 0.216]) and AI-augmented engagement ($\beta = 0.108$, $t = 2.841$, $p = 0.005$, 95% CI [0.033, 0.183]). Simple-slope analyses confirmed that the positive impacts of all three digital talent practices on employee agility were significantly stronger under high levels of digital leadership (+1 SD) compared to low levels (-1 SD).

To evaluate the specific indirect effects proposed in Hypotheses 5a, 5b, and 5c, a 5,000-subsample bootstrapping procedure was conducted. As presented in Table 7, mediation was assessed using the bootstrapped indirect effect, together with the corresponding direct and total effects. The indirect effects of DTI, CRS, and AIE on operational innovation through employee agility were statistically significant because their 95% bootstrap confidence intervals did not include zero. The type of mediation was subsequently determined based on the significance and direction of the direct and indirect effects.

Table 7: Specific Indirect Effects for Mediation (H5a, H5b, H5c)

Hypothesis	Indirect Effect	β	t	p	95% CI	Decision
H5a	DTI $\rightarrow$ EA $\rightarrow$ OI	0.107	4.215	<0.001	[0.058, 0.158]	Supported
H5b	CRS $\rightarrow$ EA $\rightarrow$ OI	0.131	4.891	<0.001	[0.079, 0.185]	Supported
H5c	AIE $\rightarrow$ EA $\rightarrow$ OI	0.099	3.982	<0.001	[0.051, 0.149]	Supported

DISCUSSION

The empirical findings of this study contribute to theoretical frameworks in strategic human resource management for digitally transforming governments, strongly supporting the theoretical assertions of Tambe et al. (2019) regarding algorithmic HR value creation. The strong validation of Hypotheses 1 and 2 confirms that transitioning from traditional personnel administration to data-driven talent ecosystems is highly effective. By utilising predictive analytics in talent acquisition and establishing continuous learning ecosystems, digital talent practices demonstrate positive linkages with employee agility. The integration of AI into HRM practices enables organisations to accurately predict employees' needs and rapidly close skill gaps (Meijerink et al., 2021). When employees recognise that algorithmic systems accurately map their competencies and provide transparent, personalised upskilling pathways, their cognitive agility significantly increases, mitigating the inherent anxiety often associated with automation (Malik et al., 2020). Furthermore, the validation of Hypothesis 3 indicates that AI-augmented engagement is positively associated with employee agility. By relieving employees of repetitive administrative burdens, AI liberates cognitive bandwidth, enabling civil servants to redirect their efforts toward proactive public service solutions, supporting the Socio-Technical Systems Theory perspective on human-AI symbiosis (Raisch & Krakowski, 2021). Comparatively, Continuous Reskilling Support ($\beta = 0.284$, $p < 0.001$) exerted a stronger influence on employee agility than Digital Talent Identification ($\beta = 0.231$, $p < 0.001$) or AI-Augmented Engagement ($\beta = 0.215$, $p < 0.001$). This finding aligns with Socio-Technical Systems Theory, indicating that while automated AI platforms reduce administrative friction, employees require direct investment in human capital to build adaptive confidence. In the context of UAE federal ministries, where technological systems are rapidly deployed under the 'We the UAE 2031' mandate, structured reskilling acts as the primary buffer against skill obsolescence anxiety, enabling civil servants to actively re-engineer operational processes

Crucially, the empirical confirmation of the mediating pathways (H5a, H5b, and H5c) demonstrates a vital socio-technical reality: digital tools remain inert without human activation. The path from employee agility to operational innovation was statistically significant and substantively meaningful ($\beta = 0.462$, $t = 9.125$, $p < 0.001$; $f^2 = 0.271$), with the associated effect size falling within the large range. The sophisticated digital talent database yields operational innovation only if it successfully induces psychological adaptability in the civil servant. Finally, the robust moderation results highlight the critical need for supervisory competence and explicitly echo the extensions of the Upper Echelons Theory proposed by Cortellazzo et al. (2019). The synergy between leadership and agility is not just advantageous but has become a strategic imperative shaping institutional norms. The capacity of digital talent interventions to foster agility is substantially amplified when leaders actively champion digital adoption, demonstrating that strategic e-leadership, combined with workforce digital competence, significantly improves organisational resilience.

CONCLUSION

This research systematically developed and empirically validated a sophisticated structural model delineating how digitalised talent management ecosystems drive operational innovation within the public sector. Moving beyond generalised human resource constructs, the study demonstrates that digital talent identification, continuous reskilling support, and AI-augmented engagement are positively related to workforce agility. The empirical architecture successfully positioned employee agility as the essential transmission mechanism translating digital HR inputs into innovation outputs, while establishing digital leadership as the critical bou-

ndary condition that maximises systemic efficacy. The findings suggest that public-sector organisations may benefit from strengthening digital leadership capabilities alongside digital talent management initiatives. Such initiatives could include leadership development, digital capability building, transparent talent analytics, and structured reskilling programmes, subject to organisational and regulatory requirements. Government entities must rapidly transition away from subjective appraisals toward transparent, AI-driven talent-mapping databases and continuous micro-learning platforms, while ensuring that robust data governance frameworks are implemented to manage ethical implications. Furthermore, promotional criteria must place heavy weight on digital leadership capabilities, as technologically resistant supervisors will actively bottleneck the innovation generated by sophisticated HR ecosystems. Future research should prioritise longitudinal methodologies to track evolving agility metrics over time, integrate objective, multi-source innovation data to overcome self-report limitations, and expand this moderated-mediation framework into developing nations to verify its generalisability globally.

Several methodological constraints should be considered when interpreting these findings. First, the cross-sectional, single-source design limits causal inference; while PLS-SEM models predictive relationships, it cannot definitively establish causality or temporal sequence. Future studies should employ longitudinal or multi-wave experimental designs to better assess how employee agility converts digital inputs into operational outcomes over time. Second, operational innovation was measured via self-reported employee perceptions rather than objective performance metrics or service-delivery KPIs. Incorporating objective organisational performance metrics would strengthen validity and more effectively mitigate concerns about common method bias. Finally, the empirical sample was drawn exclusively from UAE federal ministries. Given the specific institutional context, governance structures, and digital transformation mandates ('We the UAE 2031') of the UAE public sector, caution is warranted when generalising these results to private-sector organisations or other geographic regions.

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