AI-Analytics Capabilities and Knowledge Assimilation: Driving Innovation in SMEs

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Abstract

Purpose - This study investigates how AI-assisted big data analytics capability influences product innovation performance through digital knowledge assimilation in manufacturing SMEs in an emerging market.

Design/methodology/approach - This study employed a mixed-methods research design incorporating both qualitative and quantitative methodologies. A time-lagged, multi-stage approach was utilized to test a research model examining direct and indirect relationships between constructs. Empirical data were gathered from 292 manufacturing SMEs to validate the hypothesized relationships within the proposed framework.

Findings - AI-assisted big data analytics capability directly influences both incremental and radical product innovation performance, with a stronger effect on incremental innovation. Digital knowledge assimilation serves as a significant mediating mechanism, with stronger effects on radical innovation than incremental innovation.

Originality/value - Our findings extend dynamic capabilities view by elucidating how AI-enhanced analytical capabilities function as distinct dynamic capabilities that drive diverse innovation outcomes through knowledge assimilation processes.

Keywords - AI-assisted big data analytics capability; digital knowledge assimilation; product innovation performance; incremental product innovation; radical product innovation.

Paper type: Research paper

1. Introduction

In today's dynamic business environment, artificial intelligence (AI) has emerged as a transformative force reshaping organizational capabilities and competitive landscapes (Dwivedi *et al.*, 2021). This is particularly relevant for manufacturing small and medium enterprises (SMEs) in emerging markets, which face distinctive challenges including resource constraints, limited technological infrastructure, and intense competition while struggling with technological assimilation and pressure to innovate rapidly (Indrawati, 2020). Within this context, manufacturing SMEs face unique challenges in harnessing AI-driven capabilities to drive innovation outcomes while operating under resource constraints (Dey *et al.*, 2024). The integration of AI with big data analytics represents a particularly promising avenue for these firms to enhance their dynamic capabilities and drive product innovation performance (Fosso Wamba *et al.*, 2024).

This study conceptualizes AI-assisted big data analytics capability (ADC) as a strategic business capability that transcends conventional technological tools. Following Huang & Rust's (2018) perspective that AI should be valued as a business capability rather than merely technological advancement, ADC represents a firm's ability to select, orchestrate, and leverage AI-enhanced technologies for big data processing and transformation into competitive advantage (Abou-Foul *et al.*, 2023). This capability integrates traditional big data analytics competencies with specialized AI resources to support both incremental and radical innovation initiatives (Mikalef and Gupta, 2021). Meanwhile, digital knowledge assimilation (DKA) functions as the connective mechanism between ADC and innovation outcomes, representing digital processes through which firms analyze, classify, comprehend, and internalize information (Boroomand and Chan, 2022). This knowledge foundation manifests in two distinct dimensions: incremental product innovation performance (IPI) reflecting minor improvements to existing offerings, and radical product innovation performance (RPI) capturing fundamentally new technologies that significantly depart from existing market offerings.

Despite growing recognition of the relationship between analytics capabilities and organizational innovation (Abou-foul *et al.*, 2021; Mikalef and Gupta, 2021), considerable uncertainties persist regarding how AI-enhanced analytics specifically contributes to different innovation dimensions (Sjödin *et al.*, 2021). Most studies approach analytics from a technological infrastructure perspective, neglecting critical knowledge transformation processes through which analytics insights become innovation inputs. Current research also inadequately addresses complementary organizational capabilities needed to effectively translate analytical insights into innovative products (Lozada *et al.*, 2023). While AI technologies can enhance analytical precision and enable sophisticated customization opportunities, comprehensive frameworks connecting AI-enhanced analytics specifically to product innovation outcomes remain underdeveloped.

Building on the dynamic capabilities view (DCV) (Teece *et al.*, 1997), this study aims to investigate how ADC influences IPI and RPI through DKA in manufacturing SMEs in an emerging market. Through a time-lagged research design with 292 manufacturing SMEs, we provide a nuanced understanding of these relationships by distinguishing between incremental and radical innovation outcomes. This study makes several important contributions to theory and practice. First, we extend the dynamic capabilities literature by conceptualizing and empirically validating ADC as a distinct dynamic capability that drives both IPI and RPI. Second, we advance the understanding of the mechanisms through which ADC influences innovation outcomes by establishing DKA as a critical mediating process. Third, by examining these relationships in the context of emerging market manufacturing SMEs, we provide insights into how resource-constrained organizations can leverage AI and big data analytics to enhance innovation performance. Finally, by distinguishing between incremental and radical innovation outcomes, we offer a more nuanced understanding of how digital capabilities contribute to different types of innovation, addressing calls for more granular analyses of technology-enabled innovation (Nambisan *et al.*, 2019). These contributions are particularly timely given the accelerating digital transformation of manufacturing and the growing importance of AI as a driver of competitive advantage in data-rich environments.

2. Qualitative study

2.1. Design and methodology

The authors conducted in-depth semi-structured interviews to explore how ADC influences DKA and drive product innovation performance in SMEs. The one-on-one approach provides rich insights into managers' experiences with AI analytics implementation and innovation processes (Johnson and Rowlands, 2012). Twelve senior managers and innovation leaders from diverse SMEs participated in interviews, ranging from 25 to 40 minutes. The sample size was determined according to theoretical saturation guidelines. The interview protocol allowed participants to share their perceptions and experiences of AI analytics capabilities, knowledge assimilation processes, and their influence on innovation outcomes.

2.2. Data analysis

The interview data were analyzed using thematic analysis, following a rigorous six-step process utilizing NVivo 15.0 (Braun and Clarke, 2006). First, we familiarized ourselves with the data through repeated reading of interview transcripts. Second, we generated initial codes systematically across the entire dataset, tagging meaningful segments related to AI analytics experiences. Third, we searched for potential themes by collating codes into broader patterns, which yielded three main themes: AI-assisted big data analytics capability, digital knowledge assimilation processes, and product innovation performance outcomes. Fourth, we reviewed themes against coded extracts to ensure coherence (Gioia *et al.*, 2013). Fifth, we refined and named themes using participant quotes to substantiate interpretations. Finally, we integrated qualitative findings with existing literature to inform hypothesis development for the subsequent quantitative phase, strengthening methodological rigor through this sequential mixed-methods approach (Creswell and Clark, 2017).

2.3. Results

Our qualitative analysis (Table 1) revealed key mechanisms linking ADC to innovation performance through knowledge assimilation. Regarding AI capabilities, participants highlighted advanced data processing *("Our AI system can process customer data from multiple sources and identify patterns we never saw before" Participant 3)*, automated insight generation, and predictive analytics as core capabilities enabling competitive advantage. Concerning knowledge assimilation, participants described how AI analytics facilitates acquiring external knowledge ("AI analytics helps us scan external market data and identify emerging customer needs" Participant 2) and transforming insights into actionable strategies *("The knowledge we gain from AI analysis directly influences our product development roadmap" Participant 5)*, aligning with absorptive capacity theory (Cohen and Levinthal, 1990).

Innovation outcomes emerged as a dual construct encompassing both incremental improvements *("AI insights have led to numerous small but significant improvements in our existing product features" Participant 4)* and radical breakthroughs *("Our AI analysis revealed an entirely new market segment, leading us to develop a completely different product line" Participant*

6). These findings support DKA as a mediating mechanism between ADC and innovation performance, offering a promising theoretical framework for quantitative investigation.

==========Insert Table 1 here==========

3. Theoretical background

3.1. Dynamic capabilities view

The dynamic capabilities view (DCV) provides the theoretical foundation for examining how manufacturing SMEs utilize ADC to enhance product innovation through digital DKA. Dynamic capabilities represent an organization's ability to "integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece *et al.*, 1997), particularly relevant in digital contexts requiring constant adaptation (Warner and Wäger, 2019). Within this framework, ADC functions as an advanced sensing mechanism enabling organizations to discover innovation opportunities through AI-enabled computational analysis (Mikalef and Gupta, 2021), while DKA incorporates seizing and reconfiguring elements by converting data-derived insights into organizational knowledge critical for transforming analytics insights into innovation-relevant assets (Boroomand and Chan, 2022). Our conceptual framework proposes that ADC directly influences both innovation types while enhancing DKA, which mediates the relationship between analytics capabilities and innovation outcomes, aligning with DCV's emphasis on capability hierarchies and transformational mechanisms (Fosso Wamba *et al.*, 2024).

3.2. AI-assisted big data analytics capability

ADC represents a sophisticated organizational competency that integrates artificial intelligence technologies with big data processing to transform data streams into actionable innovation insights (Abou-Foul *et al.*, 2023). This capability is conceptualized as a firm's capacity to deploy AI-enhanced technologies for data acquisition, processing, and knowledge generation that drives product innovation outcomes (Mikalef and Gupta, 2021). ADC extends beyond traditional analytics by incorporating machine learning algorithms and natural language processing that enable automated pattern recognition and decision support (Dwivedi *et al.*, 2021). Drawing from DCV, ADC represents a specialized sensing capability allowing firms to detect market signals, customer needs, and technological opportunities (Abou-Foul *et al.*, 2023). Organizations with superior ADC can enhance innovation capabilities by identifying optimization opportunities for incremental improvements while discovering disruptive possibilities for radical innovation (Wamba *et al.*, 2020). However, effective analytics technologies require complementary capabilities that enable assimilation and application of data-derived insights within innovation processes (Mikalef and Gupta, 2021), supporting our proposition that DKA mediates the relationship between ADC and product innovation performance.

4. Literature review and hypothesis development

4.1. AI-assisted big data analytics capability and product innovation performance

DCV provides the theoretical foundation for understanding how ADC influences product innovation in emerging market manufacturing SMEs by functioning as an advanced sensing capability that enables firms to identify innovation opportunities through algorithmic data processing (Abou-Foul *et al.*, 2023). For resource-constrained SMEs, ADC represents a VRIN asset that overcomes traditional limitations in market intelligence by extracting actionable insights from diverse data sources (Mikalef *et al.*, 2019). Research demonstrates direct links between analytics capabilities and innovation performance, showing positive impacts on both incremental and radical innovation (Mikalef *et al.*, 2019; Muhammad *et al.*, 2022). AI-assisted analytics distinguishes itself through autonomous pattern identification that conventional methods might miss (Dwivedi *et al.*, 2021), particularly benefiting SMEs with limited R&D resources by enabling systematic analysis of customer feedback and market trends to identify enhancement opportunities. ADC is especially relevant for IPI, enabling systematic analysis of customer feedback, usage patterns, product performance, and market trends to identify enhancement opportunities (Kuo, 2024), with AI algorithms processing reviews, detecting failure points, and discovering unmet needs that directly inform incremental innovation initiatives.

H1: ADC positively influences IPI performance.

Beyond incremental innovation, ADC significantly impacts RPI, which involves creating products with fundamentally new technologies or value propositions (Freixanet and Rialp, 2022). Research demonstrates that big data analytics capability positively impacts RPI through business intelligence dimensions and technological opportunism (Ali *et al.*, 2025). For emerging market manufacturing SMEs, ADC enables RPI by identifying emerging technologies and novel customer needs that indicate disruptive opportunities (Orero-Blat *et al.*, 2025), facilitating discovery of unexpected correlations that inspire new product concepts, and enabling AI-powered simulation to virtually test radical innovation concepts before committing development resources (Abou-Foul *et al.*, 2023). The pattern recognition and predictive capabilities of AI are particularly valuable for identifying radical innovation opportunities (Mikalef and Gupta, 2021), enabling SMEs to establish competitive positioning in rapidly evolving global markets.

H2: ADC positively influences RPI performance.

4.2. AI-assisted big data analytics capability and digital knowledge assimilation

The knowledge-based view positions knowledge as the firm's most strategic resource, with DKA representing processes through which firms analyze, classify, and internalize analyticsderived information (Boroomand and Chan, 2022), while ADC functions as an advanced knowledge acquisition mechanism (Mikalef *et al.*, 2019). Recent evidence demonstrates that big data analytics enhances sensing agility, impacts innovation through absorptive capacity, and enhances innovation via intellectual capital (Wang *et al.*, 2023). For emerging market SMEs with limited internal knowledge resources, ADC compensates by extracting insights from external data sources, providing structure despite environmental dynamism (Mikalef and Gupta, 2021). The AI component enhances knowledge assimilation by automating initial processing, with natural language processing extracting information from unstructured sources while machine learning identifies patterns informing knowledge development (Chen and Liang, 2023).

H3: ADC positively influences DKA.

4.3. AI-assisted big data analytics capability and product innovation performance

The relationship between DKA and product innovation performance can be understood through knowledge-based theory, which positions knowledge as the firm's most strategically significant resource (Grant, 1996). DKA represents processes through which firms analyze, classify, and internalize digitally-derived information (Boroomand and Chan, 2022), particularly critical for emerging market manufacturing SMEs facing resource constraints. DKA enhances innovation by enabling systematic processing of customer feedback to identify improvement opportunities, facilitating integration of domain knowledge with data-derived insights, and promoting cross-functional knowledge sharing (Bashir and Farooq, 2019). Empirical literature supports this relationship, with studies demonstrating that absorptive capacity mediates between analytics capabilities and innovation, firms' ability to assimilate insights enhances sensing agility and innovation performance, and intellectual capital components mediate analytics-innovation relationships (Wang *et al.*, 2023). For incremental innovation, DKA enables effective processing of feedback data to identify enhancement opportunities, while for radical innovation, it facilitates assimilation of knowledge about emerging technologies and market trends indicating disruptive opportunities (Sjödin *et al.*, 2021). Business intelligence dimensions and technological opportunism further mediate relationships between analytics capabilities and breakthrough innovation (Ali *et al.*, 2025).

H4: DKA positively influences IPI performance.

H5: DKA positively influences RPI performance.

4.4. The mediating role of digital knowledge assimilation

The mediating role of DKA in the relationship between ADC and product innovation can be understood through knowledge-based view and dynamic capabilities perspective, which suggest that knowledge processes represent critical pathways through which technological capabilities translate into innovation outcomes (Grant, 1996; Teece, 2007). Recent empirical studies support this mediating relationship, with research demonstrating that dynamic capabilities, absorptive capacity, and business intelligence dimensions mediate relationships between analytics capabilities and innovation outcomes (Mikalef *et al.*, 2019; Wu *et al.*, 2024). For emerging market manufacturing SMEs, this mediation is particularly significant due to knowledge processing constraints and complex environments, with DKA providing structured mechanisms for translating analytics insights into innovation inputs (Ferraris *et al.*, 2019; Kumar *et al.*, 2020). As analytics becomes increasingly AI-driven, effective knowledge assimilation grows in importance to prevent "knowledge processing bottlenecks" where organizations struggle to apply increased insight flows (Chatterjee *et al.*, 2023). For incremental innovation, ADC generates specific insights about existing products and customer needs that are assimilated through DKA into targeted improvement initiatives, while for radical innovation, ADC identifies non-obvious patterns and emerging trends that are assimilated into novel product concepts (Ali *et al.*, 2025). This mediating relationship explains how firms with similar analytics capabilities achieve different innovation outcomes based on varying abilities to effectively assimilate insights (Adiguzel *et al.*, 2025).

H6: DKA positively mediates the relationship between ADC and IPI performance.

H7: DKA positively mediates the relationship between ADC and RPI performance.

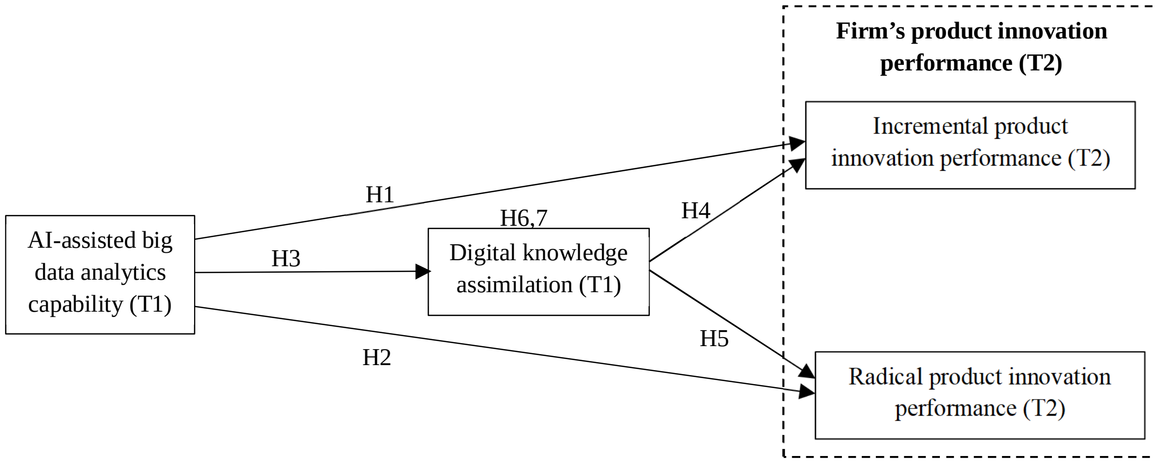

Figure 1. Conceptual model **(**Source: Authors' proposal)

5. Quantitative study

5.1. Research method

Questionnaire design

Our research instrument was developed following a comprehensive literature review and expert consultation to ensure content validity (Shareef *et al.*, 2016). The questionnaire comprised four key constructs: ADC (5 items adapted from Abou-Foul et al. (2023)), which assessed the application of AI and analytics technologies for business optimization; DKA (5 items adapted from Boroomand & Chan (2022)), which measured firms' ability to process and internalize data-derived insights; and both IPI and RPI performance (3 items each adapted from Lin et al. (2013)), which evaluated comparative innovation outcomes. All items were measured using a 5-point Likert scale ranging from strongly disagree to strongly agree to enhance measurement precision. The instrument underwent rigorous validation through a pilot study with 30 participants from emerging market manufacturing SMEs, yielding satisfactory reliability coefficients (Cronbach's alpha > 0.7) for all constructs and resulting in minor wording refinements based on respondent feedback.

Data collection

Drawing from Vietnamese manufacturing SMEs as an ideal context for studying analytics and innovation relationships in resource-constrained environments (Dey *et al.*, 2024), we partnered with the Keieijuku Vietnam Community (Kei Community), a specialized business network supported by the Japan International Cooperation Agency (JICA), accessing its network of over 1,000 manufacturing SMEs. We employed a time-lagged research design to mitigate common method bias (Podsakoff *et al.*, 2016), collecting data on ADC and DKA in phase one (Time 1), followed by IPI and RPI assessments six months later (Time 2). The survey underwent rigorous translation-back-translation procedures, with implementation via a mixed-mode approach combining online surveys, phone calls, and in-person meetings, which are appropriate for the relationship-focused Vietnamese business context (Nguyen and Rose, 2009). Our final sample included 292 valid responses (29% response rate), exceeding the recommended 5:1 ratio for SEM analysis (Hair *et al.*, 2019). Respondents represented diverse manufacturing sectors including electronics (28%), textiles (23%), food processing (18%), furniture (15%), and metal fabrication (16%), with 63% holding senior management positions and all having minimum three-year tenure ensuring familiarity with organizational capabilities.

5.3. Data analysis and results

Common method bias (CMB)

To address potential CMB concerns from single-source data collection, we performed Harman's single-factor test (Podsakoff *et al.*, 2012). Principal component analysis revealed that the first factor accounted for 33.39% of total variance, well below the 50% threshold indicating problematic CMB. Four distinct factors with eigenvalues greater than 1.0 collectively explained 62.19% of variance, confirming adequate discriminant validity among constructs and that no single factor dominated the variance structure. Additionally, we implemented procedural remedies including temporal separation of data collection with predictor variables and outcome variables measured six months apart, maintained respondent anonymity, provided clear construct definitions, and varied response formats to minimize CMB (Podsakoff *et al.*, 2012). These statistical and procedural assessments indicate that CMB is unlikely to significantly confound our findings, supporting the validity of our theoretical model examining AI analytics capabilities and knowledge assimilation processes in SMEs.

Measurement items validity

We conducted a comprehensive confirmatory factor analysis (CFA) to assess all four constructs in a saturated model revealed excellent psychometric properties with strong goodness-of-fit indices: $\chi^2(98) = 189.103$ ($\chi^2/df = 1.930$, below the 3.0 threshold); RMSEA = 0.056 (below 0.06 cutoff); SRMR = 0.050 (below 0.08 maximum); and GFI = 0.929, AGFI = 0.901, NFI = 0.891, TLI = 0.931, and CFI = 0.944 (all meeting or approaching the 0.90 threshold) (Hair *et al.*, 2021). These results validate our measurement model and establish a robust foundation for hypothesis testing.

==========Insert Table 2 here==========

Our constructs (Table 2) demonstrated strong reliability with Cronbach's alpha values (0.767-0.825) and composite reliability scores (0.853-0.877) exceeding the recommended 0.70

threshold (Hair *et al.*, 2019). Convergent validity was confirmed through substantial factor loadings (0.682-0.864) and AVE values (0.537-0.694) above the 0.5 criterion (Hair *et al.*, 2019). For discriminant validity, the Fornell-Larcker analysis showed that each construct's square root of AVE (0.733-0.833) exceeded its correlations with other constructs (Fornell and Larcker, 1981), while HTMT ratios (0.247-0.631) remained below the 0.85 threshold (Henseler *et al.*, 2015). The highest HTMT value (0.631) between DKA and RPI still maintains acceptable distinction between constructs. These results confirm our measurement model's validity and reliability.

Structural results and hypotheses testing

Our PLS inner model analysis aimed to test the proposed hypotheses. Table 3 summarizes the results, displaying path coefficients, significance values, and t-statistics for each hypothesized relationship.

==========Insert Table 3 here==========

Artificial neural network (ANN) and PROCESS Macro analysis

We employed an ANN model using PLS-SEM path results as inputs to handle non-normal distributions and capture non-linear relationships (Liébana-Cabanillas *et al.*, 2017). The feed-forward-backward-propagation algorithm with sigmoid activation functions improved predictive accuracy, utilizing 90% training /10% testing with ten-fold cross-validation (Leong *et al.*, 2018; Teo *et al.*, 2015). Low RMSE values indicate strong model fit, with Model A (DKA prediction) showing the lowest mean RMSE of 0.094 for testing, while Models B and C demonstrated acceptable predictive accuracy with mean testing RMSE values of 0.142 and 0.117 respectively (Ooi and Tan, 2016). The sensitivity analysis reveals that ADC emerges as the most critical predictor across all models with 100% normalized relative importance in Models A and C, while DKA shows high importance (100%) for IPI but moderate importance (55%) for RPI, suggesting differential pathways through which knowledge processes influence innovation outcomes. This SEM-ANN integration combined SEM's relationship testing capabilities with ANN's predictive power to reveal complex interaction patterns enriching our theoretical framework.

==========Insert Table 4 here==========

Table 4 demonstrates complete consistency between PLS-SEM and ANN importance rankings across all models. In Model A, ADC exhibits maximum (100%) importance to DKA. Model B shows both DKA (100%) and ADC (86%) significantly influencing IPI, while Model C indicates DKA (100%) and ADC (55%) affecting RPI. This perfect alignment across methodologies reinforces the validity and robustness of our identified relationships.

Using bootstrapped bias-corrected confidence intervals in PROCESS Macro (Hayes *et al.*, 2017), our mediation analysis confirms that DKA significantly mediates both hypothesized relationships. DKA mediates between ADC and IPI (indirect effect = 0.135, 95% CI [0.061, 0.226]), supporting H6, and between ADC and RPI (indirect effect = 0.159, 95% CI [0.076, 0.216]), confirming H7. These findings establish DKA as a critical mechanism through which analytics capabilities influence both innovation types.

fsQCA approach

Fuzzy-set Qualitative Comparative Analysis (fsQCA) complements PLS-SEM by examining complex configurational relationships rather than linear effects (Ragin, 2014). To calibrate our data, we transformed raw scores into fuzzy sets ranging from 0 to 1, representing degrees of membership in each condition.

Our fsQCA findings for IPI and RPI outcomes, respectively show that, for IPI, the solution demonstrates strong coverage (0.921217) and consistency (0.914402), indicating the configurations effectively explain the outcome. Three significant pathways emerged: RPI*~DKA, ~DKA*ADC, and RPI*ADC. *The third configuration (*RPI*ADC) shows the highest raw coverage (0.895375) and unique coverage (0.500364) with excellent consistency (0.929954), suggesting this combination offers the strongest explanation for IPI. For RPI, the solution exhibits good coverage (0.888687) and consistency (0.929625). Two configurations emerge: ~IPI*~DKA and IPI*ADC. The second configuration (IPI*ADC) demonstrates substantially higher raw coverage (0.870687) and unique coverage (0.739168) with strong consistency (0.938203), indicating this combination represents the dominant pathway to RPI. These findings align with the concept of equifinality in digital transformation contexts (Verhoef *et al.*, 2021), confirming multiple routes to innovation performance outcomes. Notably, the direct connection between ADC and performance indicators (both IPI and RPI) when combined with intermediary factors represents the most robust pathway.

6. Discussion and conclusion

Our findings confirm that ADC significantly enhances DKA (H1). This aligns with Mikalef et al. (2020) who found analytics capabilities strengthen organizational knowledge resources, but extends their work to the context of emerging market SMEs. Unlike Urbinati et al. (2019), who examined large organizations with established data infrastructures, our research shows resource-constrained SMEs can transform data into actionable knowledge through increasingly accessible AI-assisted analytics tools (Chatterjee *et al.*, 2021). The results demonstrate that DKA significantly impacts both IPI (H2) and RPI (H3). These findings complement Ghasemaghaei & Calic (2020), while revealing DKA has a slightly stronger effect on radical innovation, differing from Conboy et al. (2020). This may reflect emerging market SMEs' ability to "leapfrog" established technologies rather than making incremental improvements (Chen & Filieri, 2024). Our analysis confirms direct positive relationships between ADC and both IPI (H4) and RPI (H5). While Trantopoulos et al. (2017) identified a similar direct link, our study demonstrates this relationship holds for both innovation types in emerging market SMEs. The stronger direct effect on incremental innovation suggests immediate benefits for incremental improvements, while radical transformation may require mediating knowledge processes (Forés and Camisón, 2016). The mediation analysis confirms DKA significantly mediates the relationship between ADC and both IPI (H6) and RPI (H7). The stronger mediation effect for radical innovation indicates breakthrough innovations particularly depend on effective knowledge assimilation. Our fsQCA results reveal multiple pathways to innovation performance. For IPI, the configuration combining RPI and ADC demonstrates highest explanatory power. For RPI, the combination of IPI and ADC shows the strongest effect.

6.1. Theoretical implications

Our research contributes several key insights to understanding how AI-enabled analytics drives innovation in emerging markets. First, we extend DCV by validating ADC as a strategic capability influencing both incremental and radical innovation, moving beyond purely technical conceptualizations to demonstrate their role in competitive advantage (Fosso Wamba *et al.*, 2024; Mikalef and Gupta, 2021). Second, we establish DKA as the critical mediating mechanism between analytics capabilities and innovation outcomes, addressing the "black box" problem in prior literature and clarifying how data transforms into innovation knowledge (Boroomand and

Chan, 2022). Third, we distinguish between pathways to incremental versus radical innovation, showing different mechanisms and relative importance of direct versus mediated effects for IPI and RPI, answering calls for more nuanced analyses of innovation typologies (Nambisan *et al.*, 2019). Fourth, we demonstrate how resource-constrained SMEs in emerging markets can leverage AI-assisted analytics to overcome traditional innovation barriers, challenging assumptions that such capabilities are limited to large organizations in developed economies (Elia *et al.*, 2020). Finally, our configurational analysis through fsQCA reveals multiple equifinal pathways to innovation success, addressing methodological limitations in analytics research that relied solely on variable-centered approaches (Sjödin *et al.*, 2021).

6.2. Practical implications

Our findings provide several actionable implications for managers and policymakers seeking to leverage AI-assisted analytics for innovation in emerging market manufacturing SMEs. First, managers should strategically invest in AI-assisted analytics capabilities as both direct and indirect drivers of innovation performance. Our results confirm that ADC positively influences both IPI (H4) and RPI (H5), suggesting that even resource-constrained SMEs can benefit from targeted investments in analytics technologies. Rather than attempting comprehensive digital transformations, managers should prioritize analytics tools that align with their specific innovation objectives (Mikalef and Gupta, 2021). Second, organizations should develop robust knowledge assimilation processes to maximize returns from analytics investments. The significant mediating role of DKA (H6, H7) in our study highlights that simply implementing analytics technologies without corresponding knowledge management processes will limit innovation benefits. Firms should establish formal mechanisms to analyze, interpret, and internalize data-driven insights across organizational boundaries. Third, managers should tailor their analytics approaches based on their innovation goals. Our findings show that the pathways differ slightly between incremental and radical innovation, with DKA significantly impacting both IPI (H2) and RPI (H3). For incremental innovations, firms can realize quick wins through direct application of analytics insights, while radical innovations require deeper knowledge integration processes (Chaudhuri *et al.*, 2022). Fourth, policymakers in emerging economies should develop programs that enhance SMEs' access to AI technologies and build data analytics capabilities. Our results demonstrating that ADC significantly enhances DKA (H1) suggest that investments in analytics capabilities create valuable knowledge foundations, indicating that targeted support programs could help address the digital divide and boost innovation across manufacturing sectors (Elia *et al.*, 2020). Finally, educational institutions should incorporate AI and analytics training into curricula for future manufacturing managers, focusing not only on technical skills but also on knowledge management capabilities. The complementary relationship between ADC and DKA identified in our study suggests that developing both technical and knowledge management competencies is essential for maximizing innovation performance (Dwivedi *et al.*, 2021).

6.3. Limitations and future research

Despite its contributions, our study has several limitations that offer avenues for future research. First, while our time-lagged design strengthens causal inferences, fully capturing the dynamic evolution of analytics capabilities and innovation outcomes would require longer-term longitudinal studies. Second, our sample of manufacturing SMEs in emerging markets limits generalizability to other contexts; future studies should test our model across different industries and economies. Third, we focused on organizational-level capabilities, overlooking individual-level factors like data literacy that may influence innovation outcomes. Fourth, examining ADC as an aggregate construct leaves room for future research to disaggregate it into specific components to identify which elements contribute most to innovation. Finally, qualitative approaches could explore the micro-processes through which data knowledge assimilation transforms analytics insights into innovative products.

References

Abou-Foul, M., Ruiz-Alba, J.L. and López-Tenorio, P.J. (2023), "The impact of artificial intelligence capabilities on servitization: The moderating role of absorptive capacity-A dynamic capabilities perspective", *Journal of Business Research*, Vol. 157, p. 113609, doi: 10.1016/j.jbusres.2022.113609.

Abou-foul, M., Ruiz-Alba, J.L. and Soares, A. (2021), "The impact of digitalization and servitization on the financial performance of a firm: an empirical analysis", *Production Planning & Control*, Vol. 32 No. 12, pp. 975–989, doi: 10.1080/09537287.2020.1780508.

Adiguzel, Z., Sonmez Cakir, F. and Özbay, F. (2025), "Big data analytics capability and sustainability in company innovation", *International Journal of Innovation Science*, Emerald Publishing Limited.

Ali, S., Tian, H., Liu, M., Yang, X., Iqbal, S. and Akhtar, S. (2025), "Big data analytics capability and breakthrough innovation: the mediating role of technological opportunism and the moderating effect of proactive market orientation", *Journal of Enterprise Information Management*, doi: 10.1108/JEIM-09-2024-0508.

Bashir, M. and Farooq, R. (2019), "The synergetic effect of knowledge management and business model innovation on firm competence: A systematic review", *International Journal of Innovation Science*, Emerald Publishing Limited, Vol. 11 No. 3, pp. 362–387.

Boroomand, F. and Chan, Y.E. (2022), “Digital absorptive capacity: developing an instrument”, *Knowledge Management Research & Practice*, Taylor & Francis, pp. 1–12.

Braun, V. and Clarke, V. (2006), “Using thematic analysis in psychology”, *Qualitative Research in Psychology*, Vol. 3 No. 2, pp. 77–101, doi: 10.1191/1478088706qp063oa.

Chatterjee, S., Chaudhuri, R., Vrontis, D. and Giovando, G. (2023), “Digital workplace and organization performance: Moderating role of digital leadership capability”, *Journal of Innovation & Knowledge*, Vol. 8 No. 1, p. 100334, doi: 10.1016/j.jik.2023.100334.

Chatterjee, S., Rana, N.P. and Dwivedi, Y.K. (2021), “How does business analytics contribute to organisational performance and business value? A resource-based view”, *Information Technology & People*, Emerald Publishing Limited.

Chaudhuri, A., Subramanian, N. and Dora, M. (2022), “Circular economy and digital capabilities of SMEs for providing value to customers: Combined resource-based view and ambidexterity perspective”, *Journal of Business Research*, Elsevier, Vol. 142, pp. 32–44.

Chen, W. and Filieri, R. (2024), “Institutional forces, leapfrogging effects, and innovation status: Evidence from the adoption of a continuously evolving technology in small organizations”, *Technological Forecasting and Social Change*, Elsevier, Vol. 206, p. 123529.

Chen, Z. and Liang, M. (2023), “How do external and internal factors drive green innovation practices under the influence of big data analytics capability: Evidence from China”, *Journal of Cleaner Production*, Vol. 404, p. 136862, doi: 10.1016/j.jclepro.2023.136862.

Cohen, W.M. and Levinthal, D.A. (1990), “Absorptive Capacity: A New Perspective on Learning and Innovation”, *Administrative Science Quarterly*, Vol. 35 No. 1, p. 128, doi: 10.2307/2393553.

Conboy, K., Mikalef, P., Dennehy, D. and Krogstie, J. (2020), “Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda”, *European Journal of Operational Research*, Elsevier, Vol. 281 No. 3, pp. 656–672.

Creswell, J.W. and Clark, V.L.P. (2017), *Designing and Conducting Mixed Methods Research*, Sage publications.

Dey, P.K., Chowdhury, S., Abadie, A., Vann Yaroson, E. and Sarkar, S. (2024), “Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small-and medium-sized enterprises”, *International Journal of Production Research*, Taylor & Francis, Vol. 62 No. 15, pp. 5417–5456.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., *et al.* (2021), “Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy”, *International Journal of Information Management*, Elsevier, Vol. 57, p. 101994.

Elia, G., Margherita, A. and Passiante, G. (2020), “Digital entrepreneurship ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process”, *Technological Forecasting and Social Change*, Vol. 150, p. 119791, doi: 10.1016/j.techfore.2019.119791.

Ferraris, A., Mazzoleni, A., Devalle, A. and Couturier, J. (2019), “Big data analytics capabilities and knowledge management: impact on firm performance”, *Management Decision*, Vol. 57 No. 8, pp. 1923–1936, doi: 10.1108/MD-07-2018-0825.

Forés, B. and Camisón, C. (2016), “Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size?”, *Journal of Business Research*, Elsevier, Vol. 69 No. 2, pp. 831–848.

Fornell, C. and Larcker, D.F. (1981), “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error”, *JOURNAL OF MARKETING RESEARCH*, p. 12.

Fosso Wamba, S., Queiroz, M.M., Wu, L. and Sivarajah, U. (2024), “Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture”, *Annals of Operations Research*, Springer, Vol. 333 No. 2, pp. 559–578.

Freixanet, J. and Rialp, J. (2022), “Disentangling the relationship between internationalization, incremental and radical innovation, and firm performance”, *Global Strategy Journal*, Wiley Online Library, Vol. 12 No. 1, pp. 57–81.

Ghasemaghaei, M. and Calic, G. (2020), “Assessing the impact of big data on firm innovation performance: Big data is not always better data”, *Journal of Business Research*, Vol. 108, pp. 147–162, doi: 10.1016/j.jbusres.2019.09.062.

Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013), “Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology”, *Organizational Research Methods*, Vol. 16 No. 1, pp. 15–31, doi: 10.1177/1094428112452151.

Grant, R.M. (1996), “Toward a knowledge-based theory of the firm”, *Strategic Management Journal*, Vol. 17 No. S2, pp. 109–122, doi: 10.1002/smj.4250171110.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P. and Ray, S. (2021), “Evaluation of the Structural Model”, *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*, Springer International Publishing, Cham, pp. 115–138, doi: 10.1007/978-3-030-80519-7_6.

Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M. (2019), “When to use and how to report the results of PLS-SEM”, *European Business Review*, Vol. 31 No. 1, pp. 2–24, doi: 10.1108/EBR-11-2018-0203.

Hayes, A.F., Montoya, A.K. and Rockwood, N.J. (2017), "The Analysis of Mechanisms and Their Contingencies: PROCESS versus Structural Equation Modeling", *Australasian Marketing Journal*, Vol. 25 No. 1, pp. 76–81, doi: 10.1016/j.ausmj.2017.02.001.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Springer, Vol. 43 No. 1, pp. 115–135.

Indrawati, H. (2020), "Barriers to technological innovations of SMEs: how to solve them?", *International Journal of Innovation Science*, Emerald Publishing Limited, Vol. 12 No. 5, pp. 545–564.

Johnson, J.M. and Rowlands, T. (2012), "The interpersonal dynamics of in-depth interviewing", *The SAGE Handbook of Interview Research: The Complexity of the Craft*, Sage Newcastle upon Tyne, UK, pp. 99–113.

Kumar, S., Sureka, R. and Colombage, S. (2020), "Capital structure of SMEs: a systematic literature review and bibliometric analysis", *Management Review Quarterly*, Vol. 70 No. 4, pp. 535–565, doi: 10.1007/s11301-019-00175-4.

Kuo, S.-Y. (2024), "Improving innovation performance through learning capability and adaptive capability: The moderating role of big data analytics", *Knowledge Management Research & Practice*, Vol. 22 No. 4, pp. 364–376, doi: 10.1080/14778238.2023.2212182.

Leong, L.-Y., Jaafar, N.I. and Ainin, S. (2018), "Understanding Facebook commerce (f-commerce) actual purchase from an artificial neural network perspective.", *Journal of Electronic Commerce Research*, Vol. 19 No. 1.

Liébana-Cabanillas, F., Marinković, V. and Kalinić, Z. (2017), “A SEM-neural network approach for predicting antecedents of m-commerce acceptance”, *International Journal of Information Management*, Elsevier, Vol. 37 No. 2, pp. 14–24.

Lin, H., McDonough, E.F., Lin, S. and Lin, C.Y. (2013), “Managing the Exploitation/Exploration Paradox: The Role of a Learning Capability and Innovation Ambidexterity”, *Journal of Product Innovation Management*, Vol. 30 No. 2, pp. 262–278, doi: 10.1111/j.1540-5885.2012.00998.x.

Lozada, N., Arias-Pérez, J. and Henao-García, E.A. (2023), “Unveiling the effects of big data analytics capability on innovation capability through absorptive capacity: why more and better insights matter”, *Journal of Enterprise Information Management*, Emerald Publishing Limited, Vol. 36 No. 2, pp. 680–701.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019), “Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment”, *British Journal of Management*, Vol. 30 No. 2, pp. 272–298, doi: 10.1111/1467-8551.12343.

Mikalef, P. and Gupta, M. (2021), “Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance”, Elsevier, Vol. 58 No. 3, p. 103434.

Mikalef, P., Krogstie, J., Pappas, I.O. and Pavlou, P. (2020), “Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities”, *Information & Management*, Elsevier, Vol. 57 No. 2, p. 103169.

Muhammad, A., Yu, C.K., Qadir, A., Ahmed, W., Yousuf, Z. and Fan, G. (2022), "Big data analytics capability as a major antecedent of firm innovation performance", *The International Journal of Entrepreneurship and Innovation*, Vol. 23 No. 4, pp. 268–279, doi: 10.1177/14657503211050809.

Nambisan, S., Wright, M. and Feldman, M. (2019), "The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes", *Research Policy*, Elsevier, Vol. 48 No. 8, p. 103773.

Nguyen, T.V. and Rose, J. (2009), "Building trust—Evidence from Vietnamese entrepreneurs", Elsevier, Vol. 24 No. 2, pp. 165–182.

Ooi, K.-B. and Tan, G.W.-H. (2016), "Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card", *Expert Systems with Applications*, Elsevier, Vol. 59, pp. 33–46.

Orero-Blat, M., Palacios-Marqués, D., Leal-Rodriguez, A.L. and Ferraris, A. (2025), "Beyond digital transformation: a multi-mixed methods study on big data analytics capabilities and innovation in enhancing organizational performance", *Review of Managerial Science*, Springer, Vol. 19 No. 2, pp. 649–685.

Podsakoff, P.M., MacKenzie, S.B. and Podsakoff, N.P. (2012), "Sources of Method Bias in Social Science Research and Recommendations on How to Control It", *Annual Review of Psychology*, Vol. 63 No. 1, pp. 539–569, doi: 10.1146/annurev-psych-120710-100452.

Podsakoff, P.M., MacKenzie, S.B. and Podsakoff, N.P. (2016), "Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences", *Organizational Research Methods*, Sage Publications Sage CA: Los Angeles, CA, Vol. 19 No. 2, pp. 159–203.

Ragin, C.C. (2014), *The Comparative Method: Moving beyond Qualitative and Quantitative Strategies*, Univ of California Press.

Shareef, M.A., Kumar, V., Dwivedi, Y.K. and Kumar, U. (2016), “Service delivery through mobile-government (mGov): Driving factors and cultural impacts”, *Information Systems Frontiers*, Springer, Vol. 18, pp. 315–332.

Sjödin, D., Parida, V., Palmié, M. and Wincent, J. (2021), “How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops”, Elsevier, Vol. 134, pp. 574–587.

Teece, D.J. (2007), “Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance”, *Strategic Management Journal*, Vol. 28 No. 13, pp. 1319–1350, doi: 10.1002/smj.640.

Teece, D.J., Pisano, G. and Shuen, A. (1997), “Dynamic capabilities and strategic management”, *Strategic Management Journal*, Vol. 18 No. 7, pp. 509–533, doi: 10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

Teo, A.-C., Tan, G.W.-H., Ooi, K.-B., Hew, T.-S. and Yew, K.-T. (2015), “The effects of convenience and speed in m-payment”, *Industrial Management & Data Systems*, Emerald Group Publishing Limited, Vol. 115 No. 2, pp. 311–331.

Trantopoulos, K., von Krogh, G., Wallin, M.W. and Woerter, M. (2017), “External knowledge and information technology”, *MIS Quarterly*, JSTOR, Vol. 41 No. 1, pp. 287–300.

Urbinati, A., Bogers, M., Chiesa, V. and Frattini, F. (2019), “Creating and capturing value from Big Data: A multiple-case study analysis of provider companies”, *Technovation*, Elsevier, Vol. 84, pp. 21–36.

Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N. and Haenlein, M. (2021), “Digital transformation: A multidisciplinary reflection and research agenda”, *Journal of Business Research*, Vol. 122, pp. 889–901, doi: 10.1016/j.jbusres.2019.09.022.

Wamba, S.F., Dubey, R., Gunasekaran, A. and Akter, S. (2020), “The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism”, *International Journal of Production Economics*, Elsevier, Vol. 222, p. 107498.

Wang, N., Xie, W., Huang, Y. and Ma, Z. (2023), “Big Data capability and sustainability oriented innovation: The mediating role of intellectual capital”, *Business Strategy and the Environment*, Vol. 32 No. 8, pp. 5702–5720, doi: 10.1002/bse.3444.

Warner, K.S.R. and Wäger, M. (2019), “Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal”, *Long Range Planning*, Vol. 52 No. 3, pp. 326–349, doi: 10.1016/j.lrp.2018.12.001.

Wu, W., Gao, Y. and Liu, Y. (2024), “Assessing the impact of big data analytics capability on radical innovation: is business intelligence always a path?”, *Journal of Manufacturing Technology Management*, Vol. 35 No. 5, pp. 1010–1034, doi: 10.1108/JMTM-12-2023-0532.

Table 1. Coding process and theme emergence from qualitative data

Aggregate theoretical dimensions	**Second-order themes**	**First-order codes**	**Representative quotes**
AI-Assisted Big Data Analytics Capability	Advanced data processing and analysis	Implementing sophisticated analytics tools	*"Our AI system can process customer data from multiple sources and identify patterns we never saw before..." (P3)*
		Automated insight generation	*"The AI analytics automatically generates reports and highlights key trends that would take our team weeks to discover manually..." (P7)*
		Predictive analytics capabilities	*"We use machine learning algorithms to predict market demands and customer preferences with high accuracy..." (P11)*
Digital Knowledge Assimilation	Acquiring external knowledge	Identifying market opportunities	*"AI analytics helps us scan external market data and identify emerging customer needs and competitive gaps..." (P2)*
		Integrating diverse data sources	*"We combine social media data, industry reports, and customer feedback through our AI platform to get comprehensive insights..." (P8)*
	Transforming knowledge into action	Converting insights to strategies	*"The knowledge we gain from AI analysis directly influences our product development roadmap and innovation priorities..." (P5)*
		Learning from data patterns	*"AI helps us understand complex relationships in data that enable us to make more informed innovation decisions..." (P9)*
Product Innovation Performance	Incremental innovation outcomes	Continuous product improvements	*"AI insights have led to numerous small but significant improvements in our existing product features and functionality..." (P4)*
		Enhanced product quality	*"We use AI analytics to identify quality issues early and continuously refine our products based on customer usage patterns..." (P10)*
	Radical innovation outcomes	Breakthrough product development	*"Our AI analysis revealed an entirely new market segment, leading us to develop a completely different product line..." (P6)*
		Disruptive innovation capabilities	*"AI analytics helped us identify disruptive technologies and market shifts that enabled us to pioneer new solutions..." (P12)*

Source: Authors' analysis

Table 2. Measurement statistics

Items	CR	AVE	Factor loading
AI-assisted big data analytics capability (ADC), α = 0.825	0.877	0.588	
ADC1: Our company uses AI data mining capabilities and big data systems to enhance our product innovation process and bill of material.			0.833
ADC2: Our company is using machine learning models in pricing and quoting optimization.			0.759
ADC3: Our company is collecting after-sales insights and uses AI to personalize the customer experience and ensure our customers' success.			0.771
ADC4: Our company is using advanced data science in demand forecasting and stocking.			0.687
ADC5: Our company uses advanced analytics to optimize our network's resources, ensure cybersecurity and safeguard our data.			0.777
Digital knowledge assimilation (DKA), α = 0.785	0.853	0.537	
DKA1: We extensively use data analytics to fully understand market trends.			0.682
DKA2: Using data analytics, new opportunities to serve our clients are quickly understood.			0.738
DKA3: Using data analytics, we quickly analyse changing market demands.			0.754
DKA4: We quickly understand shifts in our market by analysing online data.			0.682
DKA5: We recognise the latest market trends based on the data that is available online.			0.802
Incremental product innovation performance (IPI), α = 0.767	0.866	0.682	
IPI1: We frequently introduced incremental new products into new markets in the last 3 years			0.829
IPI2: Compared to our major competitor, we introduced more incremental new products in the last 3 years.			0.798
IPI3: Compared to our major competitor, the percentage of new incremental product innovation implemented in our company in the last 3 years was greater.			0.850
Radical product innovation performance (RPI), α = 0.779	0.871	0.694	
FP1: We frequently introduced radical new products into new markets in the last 3 years.			0.859
FP2: Compared to our major competitor, we introduced more radical new products in the last 3 years.			0.864
FP3: Compared to our major competitor, the percentage of new radical product innovation implemented in our company in the last 3 years was greater.			0.771

Note(s): Cronbach's Alpha (α), Average Variance Extracted (AVE)

Source: Authors' calculation

Table 3. SEM analysis result

Hypotheses	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
H1: ADC → IPI	0.289	0.289	0.071	4.051	0.000	Accept
H2: ADC → RPI	0.231	0.233	0.074	3.121	0.002	Accept
H3: ADC → DKA	0.371	0.376	0.065	5.658	0.000	Accept
H4: DKA → IPI	0.342	0.344	0.075	4.573	0.000	Accept
H5: DKA → RPI	0.411	0.412	0.065	6.315	0.000	Accept
Mediation effects						
H6: ADC → DKA → IPI	0.127	0.130	0.039	3.215	0.001	Accept
H7: ADC → DKA → RPI	0.152	0.155	0.036	4.254	0.000	Accept
R-square adjusted						
DKA	0.137		0.134			
IPI	0.274		0.269			
RPI	0.293		0.289			

Source: Authors’ calculation

Table 4. Comparison between PLS-SEM and ANN results

PLS path	Original sample (O)/path coefficient	ANN results: Normalised relative importance (%)	Ranking (PLS-SEM) [based on path coefficient]	Ranking (ANN) [based on normalised relative importance]	Results
Model A (Output: DKA)					
ADC → DKA	0.371	100%	1	1	Match
Model B (Output: IPI)					
DKA → IPI	0.342	100%	1	1	Match
ADC → IPI	0.289	86%	2	2	Match
Model C (Output: RPI)					
DKA → RPI	0.411	100%	1	1	Match
ADC → RPI	0.231	55%	2	2	Match

Source: Authors' calculation