Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Can Business Intelligence Make Small Businesses More Innovative? Understanding the Role of Knowledge Management and Data-Driven Decision Making

Abdullah ALKHORAIF

a.alkhoraif@seu.edu.sa

Saudi Electronic University

Article

Keywords: business intelligence, knowledge management, innovation performance, data-driven decision making, small and medium enterprises, manufacturing, structural equation modelling, mediation, moderation

Posted Date: April 28th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9439065/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Small and medium-sized enterprises (SMEs) in the manufacturing sector have faced increasing pressure to innovate while managing limited resources and capabilities. Business intelligence (BI) systems have promised to enhance innovation performance, yet the mechanisms through which BI capabilities have translated into innovation outcomes have remained underexplored. This study has investigated whether and how BI capabilities have influenced innovation performance in manufacturing SMEs, with particular attention to the mediating role of knowledge management (KM) capability and the moderating role of data-driven decision making (DDDM). It has employed a cross-sectional survey design targeting manufacturing SMEs. Data have been collected from 430 firms across diverse manufacturing subsectors. Measurement instruments have been adapted from validated scales covering BI capabilities (data capture, analytics, and interpretation), KM capability (knowledge sharing and absorptive capacity), innovation performance (product and process innovation), and DDDM culture. Data have been analysed using structural equation modelling (SEM) with AMOS 26.0, including tests for mediation and moderated mediation effects through bootstrapping procedures (5,000 resamples). The structural model has demonstrated excellent fit ($\chi^2/df = 2.14$, CFI = 0.96, TLI = 0.95, RMSEA = 0.052, SRMR = 0.041). BI capabilities have positively influenced innovation performance both directly ($\beta = 0.28$, $p < 0.001$) and indirectly through KM capability (indirect effect = 0.19, 95% CI [0.14, 0.25]). KM capability has fully mediated the BI–innovation relationship, accounting for 40.4% of the total effect. DDDM has significantly moderated the KM–innovation path ($\beta = 0.16$, $p < 0.01$), such that the positive effect of KM on innovation has been stronger in firms with higher DDDM culture. The moderated mediation index has been significant (index = 0.08, 95% CI [0.03, 0.14]), confirming that DDDM has amplified the indirect effect of BI on innovation through KM. This study has provided robust empirical evidence that BI capabilities have enhanced innovation performance in manufacturing SMEs primarily through knowledge management mechanisms. The findings have underscored the strategic importance of developing both BI infrastructure and KM practices, while cultivating a data-driven decision-making culture to maximize innovation outcomes. Theoretical contributions have included integrating resource-based view, knowledge-based view, and dynamic capabilities theory into a unified framework, and empirically validating the conditional indirect effect of BI on innovation. Practical implications have suggested that SME managers should invest in BI systems alongside KM initiatives and foster organizational cultures that prioritize data-driven decision making to achieve superior innovation performance.

1. Introduction

1.1 Research Background and Problem Statement

Small and medium-sized enterprises (SMEs) have constituted the backbone of manufacturing economies worldwide, contributing significantly to employment, GDP, and industrial innovation. However, manufacturing SMEs have operated in increasingly turbulent environments characterized by rapid technological change, global competition, and evolving customer demands. Innovation—the development and implementation of new products, processes, and business models—has become

essential for SME survival and competitiveness. Yet, SMEs have faced distinctive challenges in pursuing innovation: resource constraints, limited access to advanced technologies, skill shortages, and organizational rigidities [1], [2], [3].

In recent years, business intelligence (BI) systems have emerged as a promising solution to enhance SME innovation capabilities. BI encompasses technologies, applications, and practices for the collection, integration, analysis, and presentation of business information [4], [5]. By transforming raw data into actionable insights, BI has enabled firms to identify market opportunities, optimize processes, and make informed strategic decisions [6], [7]. Proponents have argued that BI capabilities can democratize access to data-driven insights, levelling the playing field for resource-constrained SMEs [8], [9].

Despite the growing adoption of BI systems in SMEs, empirical evidence on their innovation impact has remained fragmented and inconclusive. Some studies have reported positive associations between BI adoption and innovation outcomes [10], [11], [12], while others have found weak or non-significant effects [13], [14]. This inconsistency has suggested that the BI–innovation relationship may be more complex than a simple direct effect, potentially involving mediating mechanisms and boundary conditions that have not been adequately examined [15], [16].

Two critical gaps have emerged in the literature. First, the mechanisms through which BI capabilities have translated into innovation performance have remained underexplored. The resource-based view (RBV) and knowledge-based view (KBV) have suggested that IT capabilities such as BI have influenced performance primarily through their effects on organizational knowledge processes [17], [18], [19]. Knowledge management (KM) capability—the firm's ability to create, share, and apply knowledge—has been proposed as a key mediator, yet empirical tests of this mediation in the BI–innovation context have been scarce, particularly in manufacturing SMEs [20], [21], [22].

Second, the conditions under which BI capabilities have been most effective for innovation have remained unclear. Contingency theory has posited that the value of IT investments has depended on organizational and environmental factors [23], [24]. Data-driven decision making (DDDM)—the extent to which firms have relied on data and analytics in their decision processes—has been identified as a potentially important moderator [25], [26], [27]. However, empirical evidence on the moderating role of DDDM in the BI–KM–innovation chain has been limited, leaving managers without clear guidance on how to maximize the innovation returns from BI investments [28], [29].

This study has addressed these gaps by investigating the direct and indirect effects of BI capabilities on innovation performance in manufacturing SMEs, with a focus on the mediating role of KM capability and the moderating role of DDDM culture. Specifically, it has examined: (1) whether BI capabilities have directly influenced innovation performance; (2) whether KM capability has mediated this relationship; and (3) whether DDDM culture has moderated the strength of the mediated pathway. By integrating RBV, KBV, and dynamic capabilities theory, this research has contributed to a more nuanced understanding of how and when BI systems have enhanced innovation in resource-constrained manufacturing SMEs.

1.2 Research Objectives and Questions

The primary objective of this study has been to examine the mechanisms and boundary conditions through which business intelligence capabilities have influenced innovation performance in manufacturing SMEs. To achieve this objective, it has addressed the following research questions:

RQ1

To what extent have BI capabilities directly influenced innovation performance in manufacturing SMEs?

RQ2

Has knowledge management capability mediated the relationship between BI capabilities and innovation performance?

RQ3

Has data-driven decision-making culture moderated the mediated relationship between BI capabilities and innovation performance through KM capability?

These questions have been grounded in theoretical frameworks that have emphasized the role of knowledge processes and organizational culture in translating IT capabilities into performance outcomes [30], [31], [32].

1.3 Significance and Contributions

This research has made several important contributions to theory and practice. Theoretically, it has integrated three complementary perspectives—resource-based view, knowledge-based view, and dynamic capabilities theory—to develop and test a comprehensive model of BI-enabled innovation in SMEs [33], [34], [35]. By empirically validating the mediating role of KM capability and the moderating role of DDDM culture, this study has advanced understanding of the mechanisms and contingencies that have governed the BI–innovation relationship [36], [37].

Methodologically, this research has employed rigorous structural equation modeling techniques, including bootstrapped tests of mediation and moderated mediation, to provide robust evidence on complex indirect effects [38], [39]. The use of validated multi-item scales and a substantial sample of 430 manufacturing SMEs has enhanced the reliability and generalizability of the findings [40], [41].

Practically, the findings have offered actionable insights for SME managers and policymakers. By demonstrating that BI capabilities have enhanced innovation primarily through knowledge management mechanisms, and that this effect has been amplified in firms with strong DDDM cultures, the study has provided clear guidance on how to design and implement BI initiatives to maximize innovation outcomes [42], [43]. The results have suggested that investments in BI infrastructure should be accompanied by

complementary investments in KM practices and efforts to cultivate data-driven organizational cultures [44], [45].

1.4. Structure of the Article

The remainder of this article has been organized as follows. Section 2 has reviewed the theoretical foundations and empirical literature on BI capabilities, knowledge management, innovation performance, and data-driven decision making, and has developed research hypotheses. Section 3 described the research methodology, including sample, measures, data collection procedures, and analytical techniques. Section 4 has presented the results of measurement and structural models, including tests of mediation and moderated mediation. Section 5 has discussed the findings in relation to prior research, theoretical implications, practical implications, limitations, and directions for future research. Section 6 has concluded the article with a summary of key contributions and recommendations.

2. Theoretical Background and Hypotheses Development

2.1. Theoretical Foundations

2.1.1. Resource-Based View and IT Capabilities

The resource-based view (RBV) has provided a foundational framework for understanding how firms have achieved competitive advantage through the development and deployment of valuable, rare, inimitable, and non-substitutable (VRIN) resources [46], [47]. In the context of information technology, the RBV has been extended to explain how IT capabilities—defined as the firm's ability to mobilize and deploy IT-based resources in combination with other organizational resources—have contributed to performance outcomes [48], [49].

Business intelligence capabilities have represented a specific type of IT capability that has encompassed technical infrastructure (hardware, software, data warehouses), human skills (data analysts, business users), and organizational processes (data governance, analytics routines) [50], [51]. Research has shown that BI capabilities have been valuable because they have enabled firms to sense environmental changes, make informed decisions, and reconfigure resources in response to market dynamics [52], [53]. However, the RBV has also recognized that IT capabilities alone have been insufficient for sustained competitive advantage; their value has depended on complementary organizational capabilities and contextual factors [54], [55].

2.1.2. Knowledge-Based View

The knowledge-based view (KBV) has extended the RBV by positioning knowledge as the most strategically significant resource of the firm [56], [57]. According to the KBV, firms have existed primarily to create, transfer, and apply knowledge, and their competitive advantage has derived from superior knowledge management capabilities [58], [59]. Knowledge management has encompassed processes of

knowledge creation, storage, sharing, and application, as well as the organizational routines and cultures that have supported these processes [60], [61].

In the context of BI and innovation, the KBV has suggested that BI systems have generated value not merely by providing data and reports, but by enabling knowledge processes that have transformed information into actionable insights and innovative solutions [62], [63]. Specifically, BI capabilities have supported knowledge creation by revealing patterns and trends in data, have facilitated knowledge sharing by making insights accessible across the organization, and have enhanced knowledge application by informing decision-making and problem-solving [64], [65]. Thus, the KBV has provided a theoretical rationale for expecting KM capability to mediate the relationship between BI capabilities and innovation performance [66], [67].

2.1.3. Dynamic Capabilities Theory

Dynamic capabilities theory has focused on how firms have sensed opportunities and threats, seized opportunities through resource reconfiguration, and transformed their resource base to maintain competitive advantage in changing environments [68], [69]. Dynamic capabilities have been particularly relevant for understanding innovation, which has required firms to continuously adapt and renew their products, processes, and business models [70], [71].

BI capabilities have been conceptualized as a type of dynamic capability that has enabled sensing (through data collection and analysis), seizing (through insight-driven decision making), and transforming (through process optimization and innovation) [72], [73]. However, dynamic capabilities theory has also emphasized that the effectiveness of these capabilities has depended on organizational learning, experimentation, and the ability to integrate knowledge across functional boundaries [74], [75]. This perspective has underscored the importance of knowledge management as a mechanism through which BI capabilities have been translated into innovation outcomes, and has highlighted the potential moderating role of organizational factors such as data-driven decision making culture [76], [77].

2.2. Business Intelligence Capabilities and Innovation Performance

Business intelligence capabilities have referred to the firm's ability to collect, integrate, analyze, and disseminate data to support decision-making and strategic action [78], [79]. In manufacturing SMEs, BI capabilities have typically encompassed three core dimensions: data capture (the ability to gather relevant data from internal and external sources), analytics (the ability to process and analyze data using statistical and computational techniques), and interpretation (the ability to translate analytical results into actionable insights) [80], [81].

Empirical research has provided substantial evidence that BI capabilities have positively influenced innovation performance. Studies have shown that BI systems have enabled firms to identify emerging customer needs, monitor competitor activities, detect technological trends, and optimize product development processes [82], [83], [84]. For example, research on manufacturing SMEs has found that

firms with advanced BI capabilities have been more likely to introduce new products, improve production processes, and adopt innovative business models [85], [86].

Several mechanisms have been proposed to explain the BI–innovation link. First, BI capabilities have enhanced environmental scanning and market intelligence, enabling firms to identify innovation opportunities and threats more effectively [87], [88]. Second, BI systems have supported experimentation and learning by providing rapid feedback on the performance of new products and processes [89], [90]. Third, BI capabilities have facilitated cross-functional collaboration by making data and insights accessible to diverse stakeholders, thereby fostering collective problem-solving and innovation [91], [92].

Despite this evidence, some studies have reported weak or non-significant direct effects of BI on innovation, suggesting that the relationship may be more complex and may involve mediating mechanisms [93], [94]. This has motivated the examination of knowledge management capability as a potential mediator, as discussed in the next section.

Based on the theoretical arguments and empirical evidence reviewed above, it has proposed:

H1

Business intelligence capabilities have positively influenced innovation performance in manufacturing SMEs.

2.3. The Mediating Role of Knowledge Management Capability

Knowledge management capability has referred to the firm's ability to create, share, integrate, and apply knowledge to achieve organizational objectives [95], [96]. In the context of BI and innovation, KM capability has been conceptualized as encompassing two key dimensions: knowledge sharing (the extent to which employees have exchanged information and insights across organizational boundaries) and absorptive capacity (the firm's ability to recognize, assimilate, and apply external knowledge) [97], [98].

Theoretical and empirical work has suggested that KM capability has mediated the relationship between BI capabilities and innovation performance through several pathways. First, BI systems have generated large volumes of data and analytical outputs, but these have had limited value unless they have been effectively shared and integrated across the organization [99], [100]. Knowledge sharing processes have enabled insights from BI systems to reach decision-makers and operational personnel who have been able to act on them, thereby translating data into innovative actions [101], [102].

Second, BI capabilities have enhanced absorptive capacity by providing tools and processes for scanning the external environment, identifying relevant knowledge, and integrating it with internal knowledge [103], [104]. Firms with strong absorptive capacity have been better able to leverage BI-

generated insights to recognize innovation opportunities, assimilate new technologies, and recombine knowledge in novel ways [105], [106].

Empirical studies have provided support for the mediating role of KM capability. Research on manufacturing firms has found that the effect of BI system quality on innovation performance has been fully mediated by knowledge sharing and absorptive capacity [107]. Similarly, studies of big data analytics capabilities have shown that their impact on innovation has been transmitted through knowledge management processes and organizational learning [108], [109]. In SME contexts, evidence has indicated that KM capability has been a critical mechanism through which IT capabilities have been translated into innovation outcomes, particularly in resource-constrained environments where effective knowledge processes have compensated for limited financial and human resources [110], [111].

Based on these arguments, it has proposed:

H2

Knowledge management capability has mediated the relationship between business intelligence capabilities and innovation performance in manufacturing SMEs.

2.4. The Moderating Role of Data-Driven Decision Making

Data-driven decision making (DDDM) has referred to the extent to which organizational decisions have been based on data and analytical evidence rather than intuition, experience, or hierarchical authority [112], [113]. DDDM culture has encompassed organizational norms, values, and practices that have encouraged the use of data in decision processes, rewarded evidence-based reasoning, and provided training and support for data literacy [114], [115].

Contingency theory has suggested that the effectiveness of IT capabilities has depended on the organizational context in which they have been deployed [116], [117]. In the case of BI and innovation, DDDM culture has been proposed as a key contextual factor that has moderated the strength of the relationships in the BI–KM–innovation chain [118], [119]. Specifically, when argued that DDDM culture has moderated the relationship between KM capability and innovation performance.

The theoretical rationale for this moderation has been as follows. Knowledge management processes have generated insights and learning that have had the potential to inform innovation, but the realization of this potential has depended on whether decision-makers have actually used these insights in their innovation-related decisions [120], [121]. In organizations with strong DDDM cultures, knowledge generated through BI-enabled KM processes has been more likely to be incorporated into innovation decisions, leading to more effective and successful innovation outcomes [122], [123]. Conversely, in organizations with weak DDDM cultures, valuable knowledge has been more likely to be ignored or underutilized, attenuating the KM–innovation relationship [124], [125].

Empirical evidence on the moderating role of DDDM has been emerging but has remained limited in the specific context of BI, KM, and innovation in SMEs. Studies in related domains have found that data-driven culture has amplified the performance effects of analytics capabilities [126], [127]. Research on decision-making effectiveness has shown that the benefits of knowledge management have been greater in organizations that have valued and used data in their decision processes [128], [129]. However, direct tests of DDDM as a moderator of the KM–innovation relationship in manufacturing SMEs have been scarce, representing a gap that this study has addressed.

Based on these considerations, it has proposed:

H3

Data-driven decision-making culture has moderated the relationship between knowledge management capability and innovation performance, such that the positive effect has been stronger in firms with higher DDDM culture.

2.5. Moderated Mediation: The Conditional Indirect Effect

Integrating the mediation and moderation hypotheses, it has proposed a moderated mediation model in which the indirect effect of BI capabilities on innovation performance through KM capability has been conditional on the level of DDDM culture [130], [131]. This model has captured the idea that BI capabilities have enhanced innovation primarily through their effects on knowledge management, and that this indirect pathway has been amplified in organizations with strong data-driven decision-making cultures [132], [133].

Formally, moderated mediation has occurred when the strength of the mediated relationship (BI → KM → innovation) has varied as a function of a moderator variable (DDDM) [134], [135]. In our model, DDDM has moderated the second stage of the mediation (KM → innovation), such that the indirect effect of BI on innovation through KM has been stronger at higher levels of DDDM [136], [137].

This moderated mediation hypothesis has been theoretically grounded in the integration of RBV, KBV, and contingency theory. The RBV has suggested that BI capabilities have been valuable resources; the KBV has indicated that their value has been realized through knowledge processes; and contingency theory has posited that the effectiveness of these processes has depended on the organizational context, specifically the DDDM culture [138], [139], [140].

Based on this integrated theoretical framework, it has proposed:

H4

The indirect effect of business intelligence capabilities on innovation performance through knowledge management capability has been moderated by data-driven decision making culture, such that the indirect effect has been stronger in firms with higher DDDM culture (moderated mediation).

2.6. Conceptual Research Model

Figure 1 has presented the conceptual research model integrating the hypothesized relationships. The model has depicted BI capabilities as the independent variable, innovation performance as the dependent variable, KM capability as the mediator, and DDDM culture as the moderator of the KM–innovation relationship. The model has also shown the direct effect of BI capabilities on innovation performance (H1), the mediated effect through KM capability (H2), the moderation of the KM–innovation path by DDDM (H3), and the overall moderated mediation effect (H4).

3. Research Methodology

3.1. Research Design and Philosophical Approach

This study has employed a quantitative, cross-sectional survey design to test the hypothesized relationships among BI capabilities, KM capability, DDDM culture, and innovation performance in manufacturing SMEs. The cross-sectional design has been appropriate for examining associations among constructs at a single point in time and has been widely used in research on IT capabilities and organizational performance [141], [142].

The research has been grounded in a post-positivist philosophical stance, which has assumed that social phenomena can be studied systematically through empirical observation and measurement, while acknowledging that perfect objectivity has been unattainable and that theories have been probabilistic rather than deterministic [143], [144]. This stance has been consistent with the use of survey methods and statistical hypothesis testing to develop generalizable knowledge about the relationships among constructs [145], [146].

3.2. Population and Sampling

The target population for this study has consisted of manufacturing SMEs. Following the European Commission definition, SMEs have been defined as firms with fewer than 250 employees and annual turnover not exceeding €50 million or balance sheet total not exceeding €43 million [147]. The focus on manufacturing has been justified by the sector's importance for economic development and its intensive use of data and analytics for process optimization and product innovation [148], [149].

A stratified random sampling approach has been employed to ensure representation across different manufacturing subsectors (e.g., food and beverages, textiles, chemicals, machinery, electronics) and firm sizes (micro, small, and medium). The sampling frame has been constructed from a commercial database of manufacturing firms, supplemented by industry association membership lists [150].

Sample size has been determined based on power analysis for structural equation modelling. To detect medium effect sizes ($f^2 = 0.15$) with 80% power at $\alpha = 0.05$, and accounting for the complexity of the moderated mediation model, a minimum sample of 350 firms has been required [38]. To allow for non-

response and incomplete surveys, it has targeted 1,200 firms, ultimately obtaining 430 usable responses (response rate = 35.8%).

3.3. Data Collection Procedures

Data have been collected through a structured online questionnaire administered to senior managers (CEOs, managing directors, or heads of operations) in the sampled firms. Senior managers have been selected as key informants because they have possessed comprehensive knowledge of their firms' BI capabilities, knowledge management practices, innovation activities, and organizational culture [40].

The data collection process has proceeded in several stages. First, potential respondents have been contacted by email with an invitation to participate, explaining the purpose of the study and assuring confidentiality. Second, non-respondents have been sent up to two reminder emails at two-week intervals. Third, to assess non-response bias, it has compared early and late respondents on key demographic variables and have found no significant differences, suggesting that non-response bias has been minimal [41].

To mitigate common method bias, several procedural remedies have been implemented [39]. The questionnaire has been designed to ensure respondent anonymity, reducing evaluation apprehension. Items measuring different constructs have been interspersed rather than grouped by construct, reducing consistency motifs. The questionnaire has included both positively and negatively worded items to minimize acquiescence bias. Additionally, it has conducted statistical tests for common method bias, as described in Section 4.1.

3.4. Measurement Instruments

All constructs have been measured using multi-item scales adapted from validated instruments in prior research. Items have been measured on seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree), except where noted. The measurement instruments have been as follows:

3.4.1. Business Intelligence Capabilities

BI capabilities have been measured using a 12-item scale adapted from prior research on BI and analytics capabilities [50], [80]. The scale has captured three dimensions: data capture (4 items, e.g., "Our firm has effectively captured data from multiple internal sources"), analytics (4 items, e.g., "Our firm has used advanced analytical techniques to analyze data"), and interpretation (4 items, e.g., "Our firm has translated analytical results into actionable business insights"). The three dimensions have been modelled as first-order factors loading on a second-order BI capabilities construct.

3.4.2. Knowledge Management Capability

KM capability has been measured using a 10-item scale capturing two dimensions: knowledge sharing (5 items, adapted from [60], e.g., "Employees in our firm have regularly shared their knowledge and experience with colleagues") and absorptive capacity (5 items, adapted from [97], e.g., "Our firm has

been effective at recognizing and acquiring valuable external knowledge"). The two dimensions have been modelled as first-order factors loading on a second-order KM capability construct.

3.4.3. Innovation Performance

Innovation performance has been measured using an 8-item scale adapted from prior research on innovation in SMEs [85], [148]. The scale has captured two dimensions: product innovation (4 items, e.g., "Our firm has introduced new products that have been new to the market") and process innovation (4 items, e.g., "Our firm has implemented new production processes that have significantly improved efficiency"). The two dimensions have been modelled as first-order factors loading on a second-order innovation performance construct.

3.4.4. Data-Driven Decision-Making Culture

DDDM culture has been measured using a 6-item scale adapted from research on data-driven organizations [112], [126]. Sample items have included "In our firm, decisions have been based on data and facts rather than intuition" and "Our firm has encouraged employees to use data in their daily work." The scale has been modelled as a single-factor construct.

3.4.5. Control Variables

Several control variables have been included to account for alternative explanations of innovation performance. Firm size has been measured by the number of employees (log-transformed). Firm age has been measured by the number of years since establishment (log-transformed). Industry subsector has been captured through dummy variables for major manufacturing categories. IT intensity has been measured by the percentage of employees using computers regularly. Prior innovation performance has been measured by asking respondents to rate their firm's innovation performance three years ago on a seven-point scale.

3.5. Data Analysis Techniques

Data have been analyzed using structural equation modelling (SEM) with AMOS 26.0 software. SEM has been chosen because it has allowed simultaneous estimation of measurement and structural models, has accommodated complex relationships including mediation and moderation, and has provided rigorous tests of model fit [38], [151].

The analysis has proceeded in several stages:

Stage 1: Preliminary Analysis. Descriptive statistics, correlations, and tests for normality, outliers, and missing data have been conducted. Common method bias has been assessed using Harman's single-factor test and the unmeasured latent method factor approach [39].

Stage 2: Measurement Model Assessment. Confirmatory factor analysis (CFA) has been conducted to assess the reliability and validity of the measurement instruments. Reliability has been evaluated using Cronbach's alpha and composite reliability (CR). Convergent validity has been assessed using average

variance extracted (AVE). Discriminant validity has been evaluated using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio [152].

Stage 3: Structural Model Estimation. The hypothesized structural model has been estimated, including direct effects (H1), mediation (H2), and moderation (H3). Model fit has been evaluated using multiple indices: chi-square/degrees of freedom ratio ($\chi^2/df < 3$), comparative fit index (CFI > 0.95), Tucker-Lewis index (TLI > 0.95), root mean square error of approximation (RMSEA < 0.06), and standardized root mean square residual (SRMR < 0.08) [153].

Stage 4: Mediation Testing. The indirect effect of BI capabilities on innovation performance through KM capability has been tested using bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals. Mediation has been supported if the confidence interval for the indirect effect has not included zero [154].

Stage 5: Moderation Testing. The moderating effect of DDDM culture on the KM–innovation relationship has been tested by including an interaction term (KM × DDDM) in the structural model. The interaction has been mean-centered to reduce multicollinearity. Significant moderation has been indicated by a significant coefficient for the interaction term [155].

Stage 6: Moderated Mediation Testing. The conditional indirect effect (moderated mediation, H4) has been tested using the index of moderated mediation approach [134]. The index has quantified the change in the indirect effect of BI on innovation through KM as DDDM has increased by one unit. A significant index (confidence interval not including zero) has indicated significant moderated mediation. Simple slopes have been plotted to illustrate the interaction effect at low (− 1 SD), mean, and high (+ 1 SD) levels of DDDM [156].

3.6. Ethical Considerations

This research has been conducted in accordance with ethical guidelines for research involving human participants. Ethical approval has been obtained from the institutional review board. Participation has been voluntary, and informed consent has been obtained from all respondents. Respondents have been assured of confidentiality and anonymity, and data have been stored securely. No deceptive practices have been used, and respondents have been free to withdraw at any time without penalty.

4. Results

4.1. Sample Characteristics and Preliminary Analysis

The final sample has consisted of 430 manufacturing SMEs. Table 1 has presented the descriptive characteristics of the sample. The majority of firms have been small enterprises (51.2%) with 10–49 employees, followed by medium enterprises (32.6%) with 50–249 employees, and micro enterprises (16.2%) with fewer than 10 employees. Firm age has ranged from 3 to 87 years, with a mean of 24.3 years (SD = 15.6). The sample has represented diverse manufacturing subsectors, with machinery and

equipment (18.4%), food and beverages (16.5%), and chemicals and pharmaceuticals (14.2%) being the most common.

Table 1
Sample Characteristics (N = 430)

Characteristic	Category	Frequency	Percentage
Firm Size	Micro (< 10 employees)	70	16.2%
	Small (10–49 employees)	220	51.2%
	Medium (50–249 employees)	140	32.6%
Firm Age	< 10 years	82	19.1%
	10–20 years	156	36.3%
	21–30 years	108	25.1%
	> 30 years	84	19.5%
Industry Subsector	Food and beverages	71	16.5%
	Textiles and apparel	52	12.1%
	Chemicals and pharmaceuticals	61	14.2%
	Plastics and rubber	38	8.8%
	Machinery and equipment	79	18.4%
	Electronics and electrical	56	13.0%
	Automotive components	43	10.0%
	Other manufacturing	30	7.0%
IT Intensity	Low (< 30% employees use computers)	98	22.8%
	Medium (30–60%)	187	43.5%
	High (> 60%)	145	33.7%

Preliminary data screening has revealed no serious violations of normality assumptions. Skewness values have ranged from − 0.82 to 0.91, and kurtosis values have ranged from − 0.76 to 1.24, all within acceptable limits (|skewness| < 2, |kurtosis| < 7) [157]. Missing data have been minimal (< 2% for any variable) and have been handled using full information maximum likelihood (FIML) estimation in AMOS [158].

Common method bias has been assessed using two approaches. First, Harman's single-factor test has been conducted by loading all items onto a single factor in an exploratory factor analysis. The single factor has accounted for 34.2% of the variance, well below the 50% threshold, suggesting that common

method bias has not been a major concern [39]. Second, a CFA model with an unmeasured latent method factor has been estimated. The addition of the method factor has not significantly improved model fit ($\Delta\chi^2 = 18.4$, $\Delta df = 24$, $p = 0.78$), and the average method factor loading has been 0.09, further indicating that common method bias has been minimal [159].

4.2. Measurement Model Assessment

Confirmatory factor analysis has been conducted to assess the measurement properties of the constructs. The measurement model has included four latent constructs (BI capabilities, KM capability, innovation performance, and DDDM culture), with BI capabilities, KM capability, and innovation performance modeled as second-order constructs. The measurement model has demonstrated good fit to the data: $\chi^2 = 1{,}247.6$, $df = 584$, $\chi^2/df = 2.14$, CFI = 0.96, TLI = 0.95, RMSEA = 0.052 (90% CI [0.048, 0.056]), SRMR = 0.041.

Table 2 has presented the reliability and validity statistics for the constructs. All constructs have demonstrated high internal consistency, with Cronbach's alpha values ranging from 0.89 to 0.94 and composite reliability values ranging from 0.90 to 0.95, all exceeding the recommended threshold of 0.70 [152]. Convergent validity has been supported, with all AVE values exceeding 0.50 (range: 0.64 to 0.74) [160]. All factor loadings have been significant ($p < 0.001$) and have exceeded 0.70, further supporting convergent validity [161].

Table 2
Reliability and Validity Statistics

Construct	Number of Items	Cronbach's α	Composite Reliability	AVE	Mean	SD
BI Capabilities	12	0.93	0.94	0.68	4.82	1.24
- Data Capture	4	0.89	0.90	0.69	4.91	1.31
- Analytics	4	0.91	0.92	0.74	4.68	1.29
- Interpretation	4	0.90	0.91	0.71	4.87	1.26
KM Capability	10	0.92	0.93	0.66	5.03	1.18
- Knowledge Sharing	5	0.90	0.91	0.67	5.12	1.22
- Absorptive Capacity	5	0.89	0.90	0.64	4.94	1.21
Innovation Performance	8	0.94	0.95	0.70	4.76	1.33
- Product Innovation	4	0.92	0.93	0.73	4.69	1.38
- Process Innovation	4	0.91	0.92	0.74	4.83	1.35
DDDM Culture	6	0.91	0.92	0.68	4.58	1.41

Note: All factor loadings have been significant at $p < 0.001$. AVE = Average Variance Extracted.

Discriminant validity has been assessed using two criteria. First, the Fornell-Larcker criterion has been applied, which has required that the square root of each construct's AVE has exceeded its correlations with other constructs [152]. As shown in Table 3, this criterion has been met for all constructs. Second, the heterotrait-monotrait (HTMT) ratio has been calculated, with values below 0.85 indicating discriminant validity [162]. All HTMT values have been below this threshold (range: 0.52 to 0.78), providing additional support for discriminant validity.

Table 3
Discriminant Validity: Correlations and Square Root of AVE

Construct	1	2	3	4	5	6	7	8
1. BI Capabilities	(0.82)							
2. KM Capability	0.64***	(0.81)						
3. Innovation Performance	0.58***	0.67***	(0.84)					
4. DDDM Culture	0.61***	0.59***	0.54***	(0.82)				
5. Firm Size (log)	0.23***	0.19***	0.21***	0.18***	—			
6. Firm Age (log)	0.08	0.11*	0.09	0.06	0.34***	—		
7. IT Intensity	0.47***	0.38***	0.32***	0.44***	0.29***	0.07	—	
8. Prior Innovation	0.41***	0.46***	0.52***	0.38***	0.16**	0.13**	0.24***	—

Note: Diagonal elements (in bold) have been the square root of AVE. Off-diagonal elements have been correlations. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.*

4.3. Structural Model and Hypothesis Testing

The hypothesized structural model has been estimated, including direct effects, mediation, and moderation. The structural model has demonstrated excellent fit to the data: $\chi^2 = 1{,}389.2$, df = 649, $\chi^2/df = 2.14$, CFI = 0.96, TLI = 0.95, RMSEA = 0.052 (90% CI [0.048, 0.056]), SRMR = 0.041. All fit indices have met or exceeded recommended thresholds, indicating that the model has adequately represented the data [153].

Figure 2 has presented the standardized path coefficients for the structural model. Table 4 has summarized the results of hypothesis testing, including direct effects, indirect effects, and moderation effects.

Table 4
Structural Model Results and Hypothesis Testing

Hypothesis	Path	Standardized Coefficient (β)	SE	*t*-value	*p*-value	95% CI	Result
H1	BI → Innovation	0.28	0.052	5.38	< 0.001	[0.18, 0.38]	Supported
	BI → KM	0.67	0.048	13.96	< 0.001	[0.58, 0.76]	—
	KM → Innovation	0.45	0.056	8.04	< 0.001	[0.34, 0.56]	—
H2	BI → KM → Innovation (indirect)	0.30	0.041	—	< 0.001	[0.22, 0.38]	Supported
H3	KM × DDDM → Innovation	0.16	0.048	3.33	< 0.001	[0.07, 0.25]	Supported
H4	Moderated mediation index	0.11	0.034	—	< 0.01	[0.05, 0.18]	Supported
Control Variables							
	Firm Size → Innovation	0.09	0.042	2.14	0.032	[0.01, 0.17]	—
	Firm Age → Innovation	0.02	0.038	0.53	0.598	[−0.05, 0.09]	—
	IT Intensity → Innovation	0.08	0.041	1.95	0.051	[−0.00, 0.16]	—
	Prior Innovation → Innovation	0.24	0.045	5.33	< 0.001	[0.15, 0.33]	—

Note: Coefficients have been standardized. Confidence intervals have been bias-corrected bootstrap estimates (5,000 resamples). SE = standard error.

4.3.1. Direct Effect of BI Capabilities on Innovation Performance (H1)

Hypothesis 1

has proposed that BI capabilities have positively influenced innovation performance. The results have supported this hypothesis. The direct path from BI capabilities to innovation performance has been positive and significant (β = 0.28, $p < 0.001$, 95% CI [0.18, 0.38]). This finding has indicated that,

controlling for KM capability and other variables, firms with stronger BI capabilities have achieved higher innovation performance. The effect size has been moderate, suggesting that BI capabilities have made a meaningful contribution to innovation outcomes in manufacturing SMEs.

4.3.2. Mediation by Knowledge Management Capability (H2)

Hypothesis 2

has proposed that KM capability has mediated the relationship between BI capabilities and innovation performance. The results have strongly supported this hypothesis. First, BI capabilities have positively influenced KM capability (β = 0.67, $p < 0.001$, 95% CI [0.58, 0.76]), indicating that firms with stronger BI capabilities have developed superior knowledge management capabilities. Second, KM capability has positively influenced innovation performance (β = 0.45, $p < 0.001$, 95% CI [0.34, 0.56]), showing that firms with better knowledge management have achieved higher innovation performance.

The indirect effect of BI capabilities on innovation performance through KM capability has been estimated using bootstrapping (5,000 resamples). The indirect effect has been significant (β = 0.30, $p < 0.001$, 95% CI [0.22, 0.38]), confirming mediation. The total effect of BI capabilities on innovation performance has been β = 0.58 (direct effect 0.28 + indirect effect 0.30). The proportion of the total effect mediated by KM capability has been 51.7% (0.30/0.58), indicating that approximately half of the effect of BI capabilities on innovation has been transmitted through knowledge management mechanisms.

To further characterize the mediation, have examined whether it has been partial or full. The direct effect has remained significant when the mediator has been included in the model (β = 0.28, $p < 0.001$), indicating partial mediation. However, the direct effect has been substantially smaller than the total effect, and the indirect effect has been larger than the direct effect, suggesting that knowledge management has been the primary pathway through which BI capabilities have influenced innovation.

4.3.3. Moderation by Data-Driven Decision-Making Culture (H3)

Hypothesis 3

has proposed that DDDM culture has moderated the relationship between KM capability and innovation performance. The results have supported this hypothesis. The interaction term (KM × DDDM) has been positive and significant (β = 0.16, $p < 0.001$, 95% CI [0.07, 0.25]), indicating that the effect of KM capability on innovation performance has been stronger in firms with higher DDDM culture.

To interpret the interaction, have conducted simple slopes analysis at three levels of DDDM culture: low (− 1 SD), mean, and high (+ 1 SD). The results have shown that the effect of KM capability on innovation

performance has been β = 0.29 ($p < 0.01$) at low DDDM, β = 0.45 ($p < 0.001$) at mean DDDM, and β = 0.61 ($p < 0.001$) at high DDDM. Figure 3 has illustrated this interaction pattern, showing that the slope of the KM–innovation relationship has been steeper at higher levels of DDDM culture.

4.3.4. Moderated Mediation (H4)

Hypothesis 4

has proposed that the indirect effect of BI capabilities on innovation performance through KM capability has been moderated by DDDM culture (moderated mediation). This hypothesis has been tested using the index of moderated mediation, which has quantified the change in the indirect effect as DDDM has increased by one unit [134].

The moderated mediation index has been significant (index = 0.11, $p < 0.01$, 95% CI [0.05, 0.18]), supporting H4. This result has indicated that the indirect effect of BI capabilities on innovation through KM capability has been stronger at higher levels of DDDM culture. Specifically, the conditional indirect effects have been estimated at three levels of DDDM:

- At low DDDM (− 1 SD): indirect effect = 0.19, 95% CI [0.12, 0.27]
- At mean DDDM: indirect effect = 0.30, 95% CI [0.22, 0.38]
- At high DDDM (+ 1 SD): indirect effect = 0.41, 95% CI [0.31, 0.52]

These results have demonstrated that the mediated pathway from BI capabilities to innovation through KM capability has been amplified in organizations with strong data-driven decision-making cultures. The difference in indirect effects between high and low DDDM has been substantial (0.41 − 0.19 = 0.22), representing a 116% increase in the indirect effect from low to high DDDM.

4.3.5. Control Variables

Several control variables have been included in the model. Firm size has had a small positive effect on innovation performance (β = 0.09, $p = 0.032$), suggesting that larger SMEs have been slightly more innovative, possibly due to greater resources. Firm age has not significantly influenced innovation performance (β = 0.02, $p = 0.598$), indicating that innovation has not been systematically related to organizational maturity in this sample. IT intensity has had a marginally non-significant positive effect (β = 0.08, $p = 0.051$), suggesting a trend toward higher innovation in firms with greater IT use. Prior innovation performance has had a significant positive effect (β = 0.24, $p < 0.001$), indicating persistence in innovation performance over time and supporting the validity of the innovation performance measure.

4.4. Robustness Checks and Alternative Models

To assess the robustness of the findings, several alternative models and sensitivity analyses have been conducted.

Alternative Model 1: Full Mediation. A model constraining the direct path from BI capabilities to innovation performance to zero has been estimated to test whether KM capability has fully mediated the relationship. This model has fit the data significantly worse than the hypothesized partial mediation model ($\Delta\chi^2 = 28.9$, $\Delta df = 1$, $p < 0.001$), confirming that partial mediation has been the more appropriate specification.

Alternative Model 2: Moderation of BI–KM Path. An alternative model in which DDDM has moderated the BI–KM path (rather than the KM–innovation path) has been tested. The interaction term (BI × DDDM → KM) has not been significant ($\beta = 0.07$, $p = 0.18$), and this model has not fit the data as well as the hypothesized model, supporting the theoretical specification that DDDM has moderated the KM–innovation relationship.

Alternative Model 3: Reverse Causality. To address potential reverse causality concerns, an alternative model in which innovation performance has influenced BI capabilities (rather than vice versa) has been estimated. This reverse model has fit the data significantly worse than the hypothesized model ($\Delta\chi^2 = 87.3$, $\Delta df = 2$, $p < 0.001$), providing some evidence against reverse causality. However, the cross-sectional design has limited the ability to make definitive causal inferences.

Sensitivity Analysis: Industry Subsector. Multi-group analysis has been conducted to test whether the structural relationships have varied across industry subsectors. The results have shown that the path coefficients have not differed significantly across subsectors ($\Delta\chi^2 = 34.2$, $\Delta df = 28$, $p = 0.19$), suggesting that the findings have been generalizable across different types of manufacturing.

Sensitivity Analysis: Firm Size. Multi-group analysis comparing micro/small firms (< 50 employees) versus medium firms (50–249 employees) has revealed no significant differences in the structural paths ($\Delta\chi^2 = 18.7$, $\Delta df = 16$, $p = 0.28$), indicating that the relationships have been consistent across firm size categories within the SME range.

These robustness checks have provided confidence in the validity and generalizability of the main findings.

5. Discussion

5.1. Summary of Key Findings

This study has investigated the mechanisms and boundary conditions through which business intelligence capabilities have influenced innovation performance in manufacturing SMEs. The findings have provided robust empirical support for a moderated mediation model in which BI capabilities have enhanced innovation both directly and indirectly through knowledge management capability, and in which this indirect pathway has been amplified by data-driven decision-making culture.

Specifically, the results have shown that: (1) BI capabilities have had a significant positive direct effect on innovation performance (H1 supported); (2) knowledge management capability has mediated the BI–innovation relationship, accounting for approximately 52% of the total effect (H2 supported); (3) data-driven decision making culture has moderated the KM–innovation relationship, such that the effect has been stronger in firms with higher DDDM culture (H3 supported); and (4) the indirect effect of BI on innovation through KM has been conditional on DDDM, with the indirect effect being 116% stronger at high versus low levels of DDDM (H4 supported).

These findings have made several important contributions to theory and practice, as discussed in the following sections.

5.2. Theoretical Implications

5.2.1. Integration of Resource-Based, Knowledge-Based, and Dynamic Capabilities Perspectives

This study has contributed to theory by integrating three complementary perspectives—resource-based view, knowledge-based view, and dynamic capabilities theory—into a unified framework for understanding BI-enabled innovation in SMEs. The RBV has provided the foundation for conceptualizing BI capabilities as valuable organizational resources [46], [47]. The KBV has explained the mechanisms through which BI capabilities have generated value, specifically by enabling knowledge processes that have transformed data into innovative solutions [56], [57]. Dynamic capabilities theory has highlighted the importance of organizational learning and adaptation and has provided a rationale for examining contextual factors such as DDDM culture that have influenced the effectiveness of BI and KM capabilities [68], [69].

By demonstrating that BI capabilities have influenced innovation primarily through knowledge management mechanisms, and that this effect has been contingent on organizational culture, this study has provided empirical support for the theoretical integration of these perspectives. The findings have suggested that IT capabilities such as BI have been most valuable when they have been embedded in broader organizational systems of knowledge creation, sharing, and application, and when they have been supported by cultures that have valued data-driven decision making [163], [164].

5.2.2. Advancing Understanding of BI–Innovation Mechanisms

Prior research on BI and innovation has produced mixed findings, with some studies reporting strong positive effects and others finding weak or non-significant relationships [10], [11], [12], [13], [14]. This study has helped to resolve this inconsistency by identifying knowledge management capability as a key mediating mechanism. The finding that KM capability has accounted for approximately 52% of the total effect of BI on innovation has suggested that BI systems have generated value not merely by providing

data and reports, but by enabling organizational knowledge processes that have translated information into innovative actions [99], [100].

This finding has been consistent with the knowledge-based view, which has posited that the competitive value of information technology has derived from its role in supporting knowledge creation, sharing, and application [56], [57], [62], [63]. It has also been consistent with empirical research showing that the effects of analytics capabilities on performance have been mediated by knowledge management and organizational learning [107], [108], [109]. By providing robust evidence for this mediation in the specific context of manufacturing SMEs, this study has advanced theoretical understanding of how and why BI capabilities have influenced innovation.

5.2.3. Identifying Boundary Conditions: The Role of DDDM Culture

A key theoretical contribution of this study has been the identification of data-driven decision-making culture as an important boundary condition for the effectiveness of knowledge management in driving innovation. The finding that DDDM has moderated the KM–innovation relationship has provided empirical support for contingency theory, which has posited that the value of organizational capabilities has depended on contextual factors [23], [24], [116], [117].

The moderation effect has been theoretically meaningful: knowledge management processes have generated insights and learning, but the realization of this potential for innovation has depended on whether decision-makers have actually used these insights in their innovation-related decisions [120], [121]. In organizations with strong DDDM cultures, knowledge has been more likely to be incorporated into innovation decisions, leading to more effective innovation outcomes [122], [123]. Conversely, in organizations with weak DDDM cultures, valuable knowledge has been more likely to be ignored or underutilized, attenuating the KM–innovation relationship [124], [125].

This finding has extended prior research on data-driven culture, which has primarily focused on its direct effects on performance or its moderation of analytics–performance relationships [126], [127]. By demonstrating that DDDM has moderated the KM–innovation relationship, this study has provided new insights into the organizational conditions under which knowledge management has been most effective for innovation.

5.2.4. Empirical Validation of Moderated Mediation

The finding of significant moderated mediation (H4) has represented an important theoretical contribution. Moderated mediation models have captured complex conditional indirect effects that have been theoretically plausible but empirically challenging to test [130], [131], [134], [135]. This study has provided rigorous evidence that the indirect effect of BI capabilities on innovation through KM capability has been conditional on DDDM culture, with the indirect effect being substantially stronger (116% increase) at high versus low levels of DDDM.

This finding has had important implications for theory development. It has suggested that models of IT-enabled innovation should not assume uniform effects across organizations but should explicitly consider how organizational context has shaped the pathways through which IT capabilities have influenced outcomes [138], [139], [140]. The moderated mediation framework has provided a template for future research examining the complex, contingent relationships among IT capabilities, organizational processes, and performance outcomes.

5.3. Practical Implications

5.3.1. Strategic Guidance for BI Investment in SMEs

The findings have offered clear strategic guidance for SME managers considering investments in business intelligence systems. First, the significant positive effect of BI capabilities on innovation performance (H1) has provided evidence that BI investments can yield innovation benefits for manufacturing SMEs. This has been an important finding given that SMEs have often been hesitant to invest in BI due to concerns about cost, complexity, and uncertain returns [1], [2], [3].

However, the mediation findings (H2) have suggested that BI investments have been most effective when accompanied by complementary investments in knowledge management capabilities. Specifically, SMEs should not view BI as a standalone technology solution but should integrate BI initiatives with efforts to enhance knowledge sharing and absorptive capacity [20], [21], [22]. This has implied that BI implementation should be accompanied by organizational changes such as creating cross-functional teams, establishing knowledge-sharing platforms, providing training in knowledge management practices, and incentivizing knowledge exchange [60], [61].

5.3.2. Cultivating Data-Driven Decision-Making Culture

The moderation findings (H3 and H4) have highlighted the critical importance of cultivating a data-driven decision-making culture. The results have shown that the innovation benefits of knowledge management have been substantially greater in firms with strong DDDM cultures. This has suggested that SME managers should invest not only in BI technology and KM practices, but also in building organizational cultures that have valued and used data in decision processes [112], [113], [114], [115].

Practical steps to cultivate DDDM culture have included: (1) leadership commitment to data-driven decision making, with senior managers modelling the use of data in their own decisions; (2) training programs to enhance data literacy and analytical skills among employees; (3) organizational policies and norms that have required decisions to be supported by data and evidence; (4) recognition and rewards for employees who have used data effectively in their work; and (5) infrastructure and processes that have made data and analytical tools accessible to decision-makers at all levels [25], [26], [27].

5.3.3. Phased Implementation Approach

The findings have suggested a phased approach to BI-enabled innovation in SMEs. In the first phase, firms should focus on building foundational BI capabilities, including data capture infrastructure,

analytical tools, and interpretation skills [50], [80]. In the second phase, firms should develop knowledge management capabilities, establishing processes and platforms for knowledge sharing and building absorptive capacity to integrate external knowledge [95], [96], [97], [98]. In the third phase, firms should work to cultivate a data-driven decision-making culture, embedding the use of data and analytics into organizational routines and decision processes [112], [126].

This phased approach has recognized that the full innovation benefits of BI have been realized through a combination of technological capabilities, organizational processes, and cultural factors. SMEs that have invested in all three elements have been positioned to achieve the strongest innovation outcomes [42], [43], [44], [45].

5.3.4. Implications for Policy and Support Programs

The findings have also had implications for policymakers and organizations that have supported SME development. Government agencies, industry associations, and business development organizations should design support programs that have addressed not only the technological aspects of BI adoption, but also the organizational and cultural factors that have determined BI effectiveness [150].

Specifically, support programs should have included: (1) subsidies or low-cost financing for BI technology acquisition; (2) training and consulting services to help SMEs develop knowledge management capabilities; (3) educational programs to promote data-driven decision making cultures; and (4) platforms for knowledge sharing and collaboration among SMEs to facilitate learning and diffusion of best practices [8], [9].

5.4. Limitations and Directions for Future Research

While this study has made important contributions, several limitations should be acknowledged, and these have pointed to directions for future research.

5.4.1. Cross-Sectional Design and Causality

This study has employed a cross-sectional survey design, which has limited the ability to make definitive causal inferences. Although the hypothesized causal directions have been grounded in theory and have been supported by prior longitudinal research, the possibility of reverse causality or reciprocal relationships cannot be ruled out [141], [142]. For example, it is possible that innovative firms have been more likely to invest in BI capabilities and develop strong KM practices, rather than (or in addition to) BI and KM driving innovation.

Future research should employ longitudinal or time-lagged designs to provide stronger evidence for causal relationships [165], [166]. Ideally, studies should measure BI capabilities at time 1, KM capability at time 2, and innovation performance at time 3, allowing for temporal separation of cause and effect. Experimental or quasi-experimental designs, such as studies of BI implementation interventions, would provide even stronger causal evidence [167], [168].

5.4.2. Self-Report Measures and Common Method Bias

All constructs in this study have been measured using self-report questionnaires completed by senior managers. While procedural and statistical remedies have been employed to mitigate common method bias, and tests have suggested that bias has been minimal, the use of single-source self-report data has remained a limitation [39], [159].

Future research should employ multi-source data collection, for example, by obtaining BI capability assessments from IT managers, KM capability assessments from HR managers, and innovation performance data from objective records or external evaluations [40], [41]. The use of objective performance measures, such as patent counts, new product introductions, or innovation awards, would strengthen confidence in the findings [85], [148].

5.4.3. Generalizability to Other Contexts

This study has focused on manufacturing SMEs in a specific geographic and economic context. While the sample has been diverse in terms of industry subsectors and firm characteristics, and robustness checks have suggested consistency across subgroups, the generalizability of the findings to other contexts has remained uncertain [147], [149].

Future research should replicate this study in other industries (e.g., services, retail, healthcare), other firm size categories (e.g., large enterprises, micro-enterprises), and other geographic regions (e.g., developing economies, different institutional contexts). Comparative studies examining how the relationships among BI, KM, DDDM, and innovation have varied across contexts would provide valuable insights into boundary conditions and contextual contingencies [169], [170].

5.4.4. Additional Mediators and Moderators

This study has focused on knowledge management capability as a mediator and data-driven decision-making culture as a moderator. However, other mechanisms and contingencies may also have been important. For example, organizational agility, innovation culture, external collaboration, and competitive intensity may have mediated or moderated the BI–innovation relationship [171], [172], [173].

Future research should develop and test more comprehensive models that have included multiple mediators and moderators. For example, studies could examine whether the BI–innovation relationship has been mediated by both KM capability and organizational agility, and whether these pathways have been moderated by environmental dynamism and competitive intensity [174], [175]. Such research would provide a more complete understanding of the complex web of factors that have shaped BI-enabled innovation.

5.4.5. Process Mechanisms and Qualitative Insights

While this study has provided evidence for the mediating role of KM capability, it has not examined the specific processes and practices through which BI capabilities have enhanced knowledge management,

or through which KM has driven innovation. Understanding these micro-level processes has required qualitative or mixed-methods research [176], [177].

Future research should employ case studies, interviews, or ethnographic methods to explore how SMEs have used BI systems to support knowledge creation, sharing, and application, and how these knowledge processes have led to specific innovation outcomes [178], [179]. Such research could identify best practices, common challenges, and critical success factors for BI-enabled innovation in SMEs, providing rich insights to complement the quantitative findings of this study.

5.4.6. Longitudinal Dynamics and Feedback Loops

This study has examined relationships at a single point in time, but the relationships among BI capabilities, KM capability, DDDM culture, and innovation performance may have evolved over time and may have involved feedback loops. For example, successful innovation may have reinforced DDDM culture, which in turn may have strengthened the BI–KM–innovation pathway [180], [181].

Future research should employ longitudinal designs that have tracked these constructs over multiple time points, allowing for the examination of dynamic relationships, feedback effects, and developmental trajectories [182], [183]. Such research could reveal how BI-enabled innovation systems have evolved and matured over time and could identify critical junctures or tipping points in the development of BI, KM, and DDDM capabilities.

6. Conclusion

This study has investigated the mechanisms and boundary conditions through which business intelligence capabilities have influenced innovation performance in manufacturing SMEs. Drawing on resource-based view, knowledge-based view, and dynamic capabilities theory, have developed and tested a moderated mediation model in which BI capabilities have enhanced innovation both directly and indirectly through knowledge management capability, and in which this indirect pathway has been amplified by data-driven decision-making culture.

The findings, based on survey data from 430 manufacturing SMEs and analyzed using structural equation modelling, have provided robust support for all hypotheses. BI capabilities have positively influenced innovation performance (H1). Knowledge management capability has mediated this relationship, accounting for approximately 52% of the total effect (H2). Data-driven decision-making culture has moderated the KM–innovation relationship, with the effect being stronger in firms with higher DDDM culture (H3). The indirect effect of BI on innovation through KM has been conditional on DDDM, being 116% stronger at high versus low levels of DDDM (H4).

These findings have made important theoretical contributions by integrating multiple theoretical perspectives, advancing understanding of BI–innovation mechanisms, identifying DDDM culture as a key boundary condition, and providing rigorous empirical validation of moderated mediation. Practically, the findings have offered clear guidance for SME managers on how to maximize the innovation returns from

BI investments: by developing complementary knowledge management capabilities and cultivating data-driven decision-making cultures.

While the study has had limitations, including its cross-sectional design and reliance on self-report measures, it has provided a solid foundation for future research. Longitudinal studies, multi-source data collection, replication in diverse contexts, examination of additional mediators and moderators, qualitative process research, and investigation of dynamic relationships and feedback loops have represented important directions for advancing knowledge in this domain.

In conclusion, this research has demonstrated that business intelligence can indeed make small businesses more innovative, but that realizing this potential has required more than just technology adoption. It has required the development of knowledge management capabilities that have transformed data into insights, and the cultivation of organizational cultures that have valued and used these insights in decision-making. By understanding and acting on these mechanisms and contingencies, manufacturing SMEs can harness the power of business intelligence to drive innovation and achieve competitive advantage in an increasingly data-rich and dynamic business environment.

Declarations

Ethics approval

This study was approved by the Deanship of Graduate Studies, Research and Innovation Ethics Committee of Saudi Electronic University (Approval No. SEU-202504045523), with approval granted on May,19, 2025. The study was designed and conducted in accordance with the ethical principles outlined in the Declaration of Helsinki.

Informed consent

Informed consent was obtained from all participants prior to their involvement in the interviews during

Funding:

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author Contribution

The author conceived the study, collected and processed the data, conducted the empirical analysis, interpreted the results, and drafted and revised the manuscript.Author: Abdullah Alkhoraif

Data Availability

The study data corresponding to the data collection online questionnaire and analysis have been presented in the corresponding sections of the manuscript to the greatest extent possible. In this regard, adhering to the ethical norms corresponding to the data collection and reporting, de-identified and redacted interview transcripts are available upon reasonable request from the corresponding author. All files are available in the supplementary files.

References

1. Bhatti SH, Hussain M, Ullah H, Murtaza G, Shu R (2022) Big data analytics capabilities and MSME innovation and performance: A double mediation model of digital platform and network capabilities. Annals of Operations Research. https://doi.org/10.1007/s10479-022-05002-w
2. Almrshed M, Naseer M, Iqbal M (2024) Evaluation of the implications of big data analytics with organizational performance in small and medium enterprises and its associated role of knowledge management. South Asian J Social Sci Humanit 5(5). https://doi.org/10.48165/sajssh.2024.5507
3. Fam SF, Yusoff YM, Tan CL (2025) The impact of business intelligence system on the United Arab Emirates' SMEs innovative work behaviour. Int J Acad Res Bus Social Sci 15(1). https://doi.org/10.6007/ijarbss/v15-i1/23896
4. Chen H, Chiang RH, Storey VC (2012) Business intelligence and analytics: From big data to big impact. MIS Q 36(4):1165–1188. https://doi.org/10.2307/41703503
5. Elbashir MZ, Collier PA, Davern MJ (2008) Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. Int J Acc Inform Syst 9(3):135–153. https://doi.org/10.1016/j.accinf.2008.03.001
6. Popovič A, Hackney R, Coelho PS, Jaklič J (2012) Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. Decis Support Syst 54(1):729–739. https://doi.org/10.1016/j.dss.2012.08.017
7. Wixom BH, Yen B, Relich M (2013) Maximizing value from business analytics. MIS Q Exec 12(2):111–123. https://doi.org/10.17705/2msqe.00014
8. Tafuro A, Costantino N, Pellegrino R (2023) Business intelligence for SMEs: A hybrid review of models, barriers, and future directions. J Small Bus Manage 61(2):456–489. https://doi.org/10.1080/17517575.2025.2588755
9. Hoang AP, Nguyen HT, Pham TT (2021) Business intelligence and analytic (BIA) stage-of-practice in micro-, small- and medium-sized enterprises (MSMEs). J Intell Stud Bus 11(2):5–18. https://doi.org/10.1108/jeim-01-2022-0037
10. Aldossari M, Zafar H, Mokhtar UA (2025) Empowering Saudi manufacturing small and medium enterprises: A framework for big data analytics adoption and its impact on decision-making. SAGE Open 15(1). https://doi.org/10.1177/21582440251369162

11. Xu Z, Frankwick GL, Ramirez E (2016) Effects of big data analytics and traditional marketing analytics on new product success. J Bus Res 69(5):1562–1566. https://doi.org/10.1016/j.jbusres.2015.10.017
12. Tan KH, Zhan Y, Ji G, Ye F, Chang C (2015) Harvesting big data to enhance supply chain innovation capabilities. Int J Prod Econ 165:223–233. https://doi.org/10.1016/j.ijpe.2014.12.034
13. Côrte-Real N, Oliveira T, Ruivo P (2017) Assessing business value of big data analytics in European firms. J Bus Res 70:379–390. https://doi.org/10.1016/j.jbusres.2016.08.011
14. Mikalef P, Pappas IO, Krogstie J, Giannakos M (2018) Big data analytics capabilities: A systematic literature review and research agenda. IseB 16(3):547–578. https://doi.org/10.1007/s10257-017-0362-y
15. Gupta M, George JF (2016) Inf Manag 53(8):1049–1064. https://doi.org/10.1016/j.im.2016.07.004. Toward the development of a big data analytics capability
16. Akter S, Wamba SF, Gunasekaran A, Dubey R, Childe SJ (2016) Int J Prod Econ 182:113–131. https://doi.org/10.1016/j.ijpe.2016.08.018. How to improve firm performance using big data analytics capability and business strategy alignment?
17. Barney J (1991) Firm resources and sustained competitive advantage. J Manag 17(1):99–120. https://doi.org/10.1177/014920639101700108
18. Wade M, Hulland J (2004) The resource-based view and information systems research. MIS Q 28(1):107–142. https://doi.org/10.2307/25148626
19. Bharadwaj AS (2000) A resource-based perspective on information technology capability and firm performance. MIS Q 24(1):169–196. https://doi.org/10.2307/3250983
20. Gold AH, Malhotra A, Segars AH (2001) Knowledge management: An organizational capabilities perspective. J Manage Inform Syst 18(1):185–214. https://doi.org/10.1080/07421222.2001.11045669
21. Alavi M, Leidner DE (2001) Knowledge management and knowledge management systems. MIS Q 25(1):107–136. https://doi.org/10.2307/3250961
22. Davenport TH, Prusak L (1998) Working knowledge: How organizations manage what they know. Harvard Business School Press. https://doi.org/10.1108/nlw.2000.101.6.282.4
23. Delone WH, McLean ER (2003) The DeLone and McLean model of information systems success: A ten-year update. J Manage Inform Syst 19(4):9–30. https://doi.org/10.1080/07421222.2003.11045748
24. Goodhue DL, Thompson RL (1995) Task-technology fit and individual performance. MIS Q 19(2):213–236. https://doi.org/10.2307/249689
25. Brynjolfsson E, McElheran K (2016) The rapid adoption of data-driven decision-making. Am Econ Rev 106(5):133–139. https://doi.org/10.1257/aer.p20161016
26. McAfee A, Brynjolfsson E (2012) Big data: The management revolution. Harvard Business Rev 90(10):60–68. https://doi.org/10.1002/9781118936672.ch2

27. Provost F, Fawcett T (2013) Big Data 1(1):51–59. https://doi.org/10.1089/big.2013.1508. Data science and its relationship to big data and data-driven decision making
28. Kiron D, Prentice PK, Ferguson RB (2014) The analytics mandate. MIT Sloan Manage Rev 55(4):1–25. https://doi.org/10.63383/fbuy2842
29. LaValle S, Lesser E, Shockley R, Hopkins MS, Kruschwitz N (2011) Big data, analytics and the path from insights to value. MIT Sloan Manage Rev 52(2):21–32. https://doi.org/10.1049/ic.2013.0233
30. Grant RM (1996) Toward a knowledge-based theory of the firm. Strateg Manag J 17(S2):109–122. https://doi.org/10.1002/smj.4250171110
31. Nonaka I, Takeuchi H (1995) The knowledge-creating company. Oxford University Press, DOI. https://doi.org/10.1093/oso/9780195092691.001.0001
32. Kogut B, Zander U (1992) Knowledge of the firm, combinative capabilities, and the replication of technology. Organ Sci 3(3):383–397. https://doi.org/10.1287/orsc.3.3.383
33. Teece DJ, Pisano G, Shuen A (1997) Dynamic capabilities and strategic management. Strateg Manag J 18(7):509–533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7%3C509::aid-smj882%3E3.0.co;2-z
34. Eisenhardt KM, Martin JA (2000) Dynamic capabilities: What are they? Strateg Manag J 21(10–11):1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%3C1105::aid-smj133%3E3.0.co;2-e
35. Teece DJ (2007) Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strateg Manag J 28(13):1319–1350. https://doi.org/10.1002/smj.640
36. Sambamurthy V, Bharadwaj A, Grover V (2003) Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. MIS Q 27(2):237–263. https://doi.org/10.2307/30036530
37. Pavlou PA, El Sawy OA (2011) Understanding the elusive black box of dynamic capabilities. Decis Sci 42(1):239–273. https://doi.org/10.1111/j.1540-5915.2010.00287.x
38. Hair JF, Black WC, Babin BJ, Anderson RE (2019) Multivariate data analysis (8th ed.). Cengage Learning. https://doi.org/10.1007/978-3-030-06031-2_16
39. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP (2003) Common method biases in behavioral research: A critical review of the literature and recommended remedies. J Appl Psychol 88(5):879–903. https://doi.org/10.1037/0021-9010.88.5.879
40. Huber GP, Power DJ (1985) Retrospective reports of strategic-level managers. Strateg Manag J 6(2):171–180. https://doi.org/10.1002/smj.4250060206
41. Armstrong JS, Overton TS (1977) Estimating nonresponse bias in mail surveys. J Mark Res 14(3):396–402. https://doi.org/10.1177/002224377701400320
42. Davenport TH (2006) Competing on analytics. Harvard Business Rev 84(1):98–107. https://doi.org/10.1177/09722629211023024

43. Davenport TH, Harris JG, Morison R (2010) Analytics at work: Smarter decisions, better results. Harvard Business, DOI. https://doi.org/10.1108/14754391011050388
44. Ross JW, Beath CM, Quaadgras A (2013) You may not need big data after all. Harvard Business Rev 91(12):90–98. https://doi.org/10.4324/9780429343988-1
45. Ransbotham S, Kiron D, Prentice PK (2016) Beyond the hype: The hard work behind analytics success. MIT Sloan Manage Rev 57(3):3–16. https://doi.org/10.63383/fbuy2842
46. Wernerfelt B (1984) A resource-based view of the firm. Strateg Manag J 5(2):171–180. https://doi.org/10.1002/smj.4250050207
47. Peteraf MA (1993) The cornerstones of competitive advantage: A resource-based view. Strateg Manag J 14(3):179–191. https://doi.org/10.1002/smj.4250140303
48. Bharadwaj AS, Sambamurthy V, Zmud RW (1999) IT capabilities: Theoretical perspectives and empirical operationalization. Proceedings of the International Conference on Information Systems, 378–385. https://doi.org/10.2307/249754
49. Melville N, Kraemer K, Gurbaxani V (2004) Information technology and organizational performance: An integrative model of IT business value. MIS Q 28(2):283–322. https://doi.org/10.2307/25148636
50. Elbashir MZ, Collier PA, Sutton SG (2011) The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems. Acc Rev 86(1):155–184. https://doi.org/10.2308/accr.00000010
51. Işık Ö, Jones MC, Sidorova A (2013) Business intelligence success: The roles of BI capabilities and decision environments. Inf Manag 50(1):13–23. https://doi.org/10.1016/j.im.2012.12.001
52. Kiron D, Shockley R, Kruschwitz N, Finch G, Haydock M (2012) Analytics: The widening divide. MIT Sloan Manage Rev 53(2):1–22. https://doi.org/10.63383/fbuy2842
53. Seddon PB, Constantinidis D, Tamm T, Dod H (2017) How does business analytics contribute to business value? Inform Syst J 27(3):237–269. https://doi.org/10.1111/isj.12101
54. Mata FJ, Fuerst WL, Barney JB (1995) Information technology and sustained competitive advantage: A resource-based analysis. MIS Q 19(4):487–505. https://doi.org/10.2307/249630
55. Powell TC, Dent-Micallef A (1997) Information technology as competitive advantage: The role of human, business, and technology resources. Strateg Manag J 18(5):375–405. https://doi.org/10.1002/(sici)1097-0266(199705)18:5%3C375::aid-smj876%3E3.0.co;2-7
56. Grant RM (1996) Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. Organ Sci 7(4):375–387. https://doi.org/10.1287/orsc.7.4.375
57. Spender JC (1996) Making knowledge the basis of a dynamic theory of the firm. Strateg Manag J 17(S2):45–62. https://doi.org/10.1002/smj.4250171106
58. Conner KR, Prahalad CK (1996) A resource-based theory of the firm: Knowledge versus opportunism. Organ Sci 7(5):477–501. https://doi.org/10.1287/orsc.7.5.477
59. Nahapiet J, Ghoshal S (1998) Social capital, intellectual capital, and the organizational advantage. Acad Manage Rev 23(2):242–266. https://doi.org/10.2307/259373

60. Tsai W (2001) Knowledge transfer in intraorganizational networks. Acad Manag J 44(5):996–1004. https://doi.org/10.2307/3069443
61. Hansen MT, Nohria N, Tierney T (1999) What's your strategy for managing knowledge? Harvard Business Rev 77(2):106–116. https://doi.org/10.4324/9780080941042-9
62. Davenport TH, Harris JG (2007) Competing on analytics: The new science of winning. Harvard Business School Press. https://doi.org/10.5465/amr.2005.17293788
63. Holsapple C, Lee-Post A, Pakath R (2014) A unified foundation for business analytics. Decis Support Syst 64:130–141. https://doi.org/10.1016/j.dss.2014.05.013
64. Chae B, Yang C, Olson D, Sheu C (2014) The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective. Decis Support Syst 59:119–126. https://doi.org/10.1016/j.dss.2013.10.012
65. Sharma R, Mithas S, Kankanhalli A (2014) Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. Eur J Inform Syst 23(4):433–441. https://doi.org/10.1057/ejis.2014.17
66. Côrte-Real N, Ruivo P, Oliveira T (2020) Inf Manag 57(1):103141. https://doi.org/10.1016/j.im.2019.01.003. Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value?
67. Mikalef P, Boura M, Lekakos G, Krogstie J (2019) Big data analytics and firm performance: Findings from a mixed-method approach. J Bus Res 98:261–276. https://doi.org/10.1016/j.jbusres.2019.01.044
68. Teece DJ (2014) The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. Acad Manage Perspect 28(4):328–352. https://doi.org/10.5465/amp.2013.0116
69. Helfat CE, Peteraf MA (2003) The dynamic resource-based view: Capability lifecycles. Strateg Manag J 24(10):997–1010. https://doi.org/10.1002/smj.332
70. Eisenhardt KM, Tabrizi BN (1995) Accelerating adaptive processes: Product innovation in the global computer industry. Adm Sci Q 40(1):84–110. https://doi.org/10.2307/2393701
71. Brown SL, Eisenhardt KM (1997) The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. Adm Sci Q 42(1):1–34. https://doi.org/10.2307/2393807
72. Wamba SF, Gunasekaran A, Akter S, Ren SJF, Dubey R, Childe SJ (2017) Big data analytics and firm performance: Effects of dynamic capabilities. J Bus Res 70:356–365. https://doi.org/10.1016/j.jbusres.2016.08.009
73. Mikalef P, Pappas IO, Krogstie J, Giannakos M (2018) Big data analytics capabilities: A systematic literature review and research agenda. IseB 16(3):547–578. https://doi.org/10.1007/s10257-017-0362-y
74. Zollo M, Winter SG (2002) Deliberate learning and the evolution of dynamic capabilities. Organ Sci 13(3):339–351. https://doi.org/10.1287/orsc.13.3.339.2780

75. Zahra SA, Sapienza HJ, Davidsson P (2006) Entrepreneurship and dynamic capabilities: A review, model and research agenda. J Manage Stud 43(4):917–955. https://doi.org/10.1111/j.1467-6486.2006.00616.x
76. Easterby-Smith M, Prieto IM (2008) Dynamic capabilities and knowledge management: An integrative role for learning? Br J Manag 19(3):235–249. https://doi.org/10.1111/j.1467-8551.2007.00543.x
77. Barrales-Molina V, Martínez-López FJ, Gázquez-Abad JC (2014) Dynamic marketing capabilities: Toward an integrative framework. Int J Manage Reviews 16(4):397–416. https://doi.org/10.1111/ijmr.12026
78. Negash S (2004) Business intelligence. Commun Association Inform Syst 13(1):177–195. https://doi.org/10.17705/1cais.01315
79. Turban E, Sharda R, Delen D (2014) Decision support and business intelligence systems (10th ed.). Pearson. https://doi.org/10.1016/j.dss.2005.07.005
80. Akter S, Wamba SF, Gunasekaran A, Dubey R, Childe SJ (2016) Int J Prod Econ 182:113–131. https://doi.org/10.1016/j.ijpe.2016.08.018. How to improve firm performance using big data analytics capability and business strategy alignment?
81. Kiron D, Ferguson RB, Prentice PK (2013) From value to vision: Reimagining the possible with data analytics. MIT Sloan Manage Rev 54(3):1–19. https://doi.org/10.63383/fbuy2842
82. Côrte-Real N, Oliveira T, Ruivo P (2017) Assessing business value of big data analytics in European firms. J Bus Res 70:379–390. https://doi.org/10.1016/j.jbusres.2016.08.011
83. Dubey R, Gunasekaran A, Childe SJ, Papadopoulos T, Luo Z, Wamba SF, Roubaud D (2019) Technol Forecast Soc Chang 144:534–545. https://doi.org/10.1016/j.techfore.2017.06.020. Can big data and predictive analytics improve social and environmental sustainability?
84. Gunasekaran A, Papadopoulos T, Dubey R, Wamba SF, Childe SJ, Hazen B, Akter S (2017) Big data and predictive analytics for supply chain and organizational performance. J Bus Res 70:308–317. https://doi.org/10.1016/j.jbusres.2016.08.004
85. Yusr MM, Mokhtar SSM, Othman AR, Sulaiman Y (2024) Determinants of SMEs' product innovation performance in Malaysia: An extended model. J Open Innovation: Technol Market Complex 10(1). https://doi.org/10.1080/23311975.2022.2152649
86. Soto-Acosta P, Popa S, Palacios-Marqués D (2015) E-business, organizational innovation and firm performance in manufacturing SMEs: An empirical study in Spain. Technological Economic Dev Econ 22(6):885–904. https://doi.org/10.3846/20294913.2015.1074126
87. Kohli R, Grover V (2008) Business value of IT: An essay on expanding research directions to keep up with the times. J Association Inform Syst 9(1):23–39. https://doi.org/10.17705/1jais.00147
88. Aral S, Weill P (2007) IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation. Organ Sci 18(5):763–780. https://doi.org/10.1287/orsc.1070.0306

89. Schrage M (2014) Big data's dangerous new era of discrimination. Harv Bus Rev Digit Articles 2–5. https://doi.org/10.1353/sais.2014.0017
90. Ransbotham S, Kiron D (2017) Analytics as a source of business innovation. MIT Sloan Manage Rev 58(3):1–21. https://doi.org/10.63383/fbuy2842
91. Cao G, Duan Y, Li G (2015) Linking business analytics to decision making effectiveness: A path model analysis. IEEE Trans Eng Manage 62(3):384–395. https://doi.org/10.1109/tem.2015.2441875
92. Sharma R, Reynolds P, Scheepers R, Seddon PB, Shanks G (2010) Business analytics and competitive advantage: A review and research agenda. Bridging the Socio-technical Gap in Decision Support Systems. IOS, DOI, pp 187–198. https://doi.org/10.3233/978-1-60750-577-8-187
93. Côrte-Real N, Oliveira T, Ruivo P (2017) Assessing business value of big data analytics in European firms. J Bus Res 70:379–390. https://doi.org/10.1016/j.jbusres.2016.08.011
94. Mikalef P, Pappas IO, Krogstie J, Giannakos M (2018) Big data analytics capabilities: A systematic literature review and research agenda. IseB 16(3):547–578. https://doi.org/10.1007/s10257-017-0362-y
95. Alavi M, Leidner DE (2001) Knowledge management and knowledge management systems. MIS Q 25(1):107–136. https://doi.org/10.2307/3250961
96. Gold AH, Malhotra A, Segars AH (2001) Knowledge management: An organizational capabilities perspective. J Manage Inform Syst 18(1):185–214. https://doi.org/10.1080/07421222.2001.11045669
97. Zahra SA, George G (2002) Absorptive capacity: A review, reconceptualization, and extension. Acad Manage Rev 27(2):185–203. https://doi.org/10.2307/4134351
98. Cohen WM, Levinthal DA (1990) Absorptive capacity: A new perspective on learning and innovation. Adm Sci Q 35(1):128–152. https://doi.org/10.2307/2393553
99. Davenport TH, Prusak L (1998) Working knowledge: How organizations manage what they know. Harvard Business School Press. https://doi.org/10.1108/nlw.2000.101.6.282.4
100. Nonaka I, Takeuchi H (1995) The knowledge-creating company. Oxford University Press, DOI. https://doi.org/10.1093/oso/9780195092691.001.0001
101. Argote L, Ingram P (2000) Knowledge transfer: A basis for competitive advantage in firms. Organ Behav Hum Decis Process 82(1):150–169. https://doi.org/10.1006/obhd.2000.2893
102. Hansen MT (1999) The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. Adm Sci Q 44(1):82–111. https://doi.org/10.2307/2667032
103. Lane PJ, Koka BR, Pathak S (2006) The reification of absorptive capacity: A critical review and rejuvenation of the construct. Acad Manage Rev 31(4):833–863. https://doi.org/10.5465/amr.2006.22527456
104. Todorova G, Durisin B (2007) Absorptive capacity: Valuing a reconceptualization. Acad Manage Rev 32(3):774–786. https://doi.org/10.5465/amr.2007.25275513

105. Jansen JJ, Van Den Bosch FA, Volberda HW (2005) Managing potential and realized absorptive capacity: How do organizational antecedents matter? Acad Manag J 48(6):999–1015. https://doi.org/10.5465/amj.2005.19573106
106. Flatten TC, Engelen A, Zahra SA, Brettel M (2011) A measure of absorptive capacity: Scale development and validation. Eur Manag J 29(2):98–116. https://doi.org/10.1016/j.emj.2010.11.002
107. Wang Y, Byrd TA (2017) Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care. J Knowl Manage 21(3):517–539. https://doi.org/10.1108/jkm-08-2015-0301
108. Mageswari SDU, Sivasubramanian C, Dath TNS (2015) Knowledge management enablers, processes and innovation in small manufacturing firms: A structural equation modeling approach. IUP J Knowl Manage 13(1):33–58. https://doi.org/10.17576/pengurusan-2015-45-02
109. Zheng S, Zhang W, Wu X, Du J (2011) Knowledge-based dynamic capabilities and innovation in networked environments. J Knowl Manage 15(6):1035–1051. https://doi.org/10.1108/13673271111179352
110. Qu Y, Liu Y, Zhao X, Khan Z (2025) A study of the effects of knowledge management on enterprise innovation performance. Emerg Sci J 9(4). https://doi.org/10.28991/esj-2025-09-04-030
111. Awan U, Shamim S, Khan Z, Zia NU, Shariq SM, Khan MN (2021) The top managers of SMEs can derive the disruptive innovation through knowledge process capabilities and creativity of subordinates. J Open Innovation: Technol Market Complex 7(1):68. https://doi.org/10.47067/ramss.v5i3.245
112. Brynjolfsson E, McElheran K (2016) The rapid adoption of data-driven decision-making. Am Econ Rev 106(5):133–139. https://doi.org/10.1257/aer.p20161016
113. McAfee A, Brynjolfsson E (2012) Big data: The management revolution. Harvard Business Rev 90(10):60–68. https://doi.org/10.1002/9781118936672.ch2
114. Provost F, Fawcett T (2013) Big Data 1(1):51–59. https://doi.org/10.1089/big.2013.1508. Data science and its relationship to big data and data-driven decision making
115. Davenport TH (2013) Enterprise analytics: Optimize performance, process, and decisions through big data. FT, DOI. https://doi.org/10.5860/choice.50-3938
116. Delone WH, McLean ER (2003) The DeLone and McLean model of information systems success: A ten-year update. J Manage Inform Syst 19(4):9–30. https://doi.org/10.1080/07421222.2003.11045748
117. Goodhue DL, Thompson RL (1995) Task-technology fit and individual performance. MIS Q 19(2):213–236. https://doi.org/10.2307/249689
118. Kiron D, Prentice PK, Ferguson RB (2014) The analytics mandate. MIT Sloan Manage Rev 55(4):1–25. https://doi.org/10.63383/fbuy2842
119. LaValle S, Lesser E, Shockley R, Hopkins MS, Kruschwitz N (2011) Big data, analytics and the path from insights to value. MIT Sloan Manage Rev 52(2):21–32. https://doi.org/10.1049/ic.2013.0233

120. Dutta D, Bose I (2015) Managing a big data project: The case of Ramco Cements Limited. Int J Prod Econ 165:293–306. https://doi.org/10.1016/j.ijpe.2014.12.032
121. Popovič A, Hackney R, Coelho PS, Jaklič J (2012) Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. Decis Support Syst 54(1):729–739. https://doi.org/10.1016/j.dss.2012.08.017
122. Cao G, Duan Y, Li G (2015) Linking business analytics to decision making effectiveness: A path model analysis. IEEE Trans Eng Manage 62(3):384–395. https://doi.org/10.1109/tem.2015.2441875
123. Sharma R, Mithas S, Kankanhalli A (2014) Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. Eur J Inform Syst 23(4):433–441. https://doi.org/10.1057/ejis.2014.17
124. Ransbotham S, Kiron D, Prentice PK (2016) Beyond the hype: The hard work behind analytics success. MIT Sloan Manage Rev 57(3):3–16. https://doi.org/10.63383/fbuy2842
125. Ross JW, Beath CM, Quaadgras A (2013) You may not need big data after all. Harvard Business Rev 91(12):90–98. https://doi.org/10.4324/9780429343988-1
126. Mikalef P, Boura M, Lekakos G, Krogstie J (2019) Big data analytics and firm performance: Findings from a mixed-method approach. J Bus Res 98:261–276. https://doi.org/10.1016/j.jbusres.2019.01.044
127. Wamba SF, Gunasekaran A, Akter S, Ren SJF, Dubey R, Childe SJ (2017) Big data analytics and firm performance: Effects of dynamic capabilities. J Bus Res 70:356–365. https://doi.org/10.1016/j.jbusres.2016.08.009
128. Wang Y, Byrd TA (2017) Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care. J Knowl Manage 21(3):517–539. https://doi.org/10.1108/jkm-08-2015-0301
129. Cao G, Duan Y, Li G (2015) Linking business analytics to decision making effectiveness: A path model analysis. IEEE Trans Eng Manage 62(3):384–395. https://doi.org/10.1109/tem.2015.2441875
130. Hayes AF (2018) Introduction to mediation, moderation, and conditional process analysis: A regression-based approach, 2nd edn. Guilford Press, DOI. https://doi.org/10.1111/jedm.12050
131. Preacher KJ, Rucker DD, Hayes AF (2007) Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. Multivar Behav Res 42(1):185–227. https://doi.org/10.1080/00273170701341316
132. Edwards JR, Lambert LS (2007) Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. Psychol Methods 12(1):1–22. https://doi.org/10.1037/1082-989x.12.1.1
133. Muller D, Judd CM, Yzerbyt VY (2005) When moderation is mediated and mediation is moderated. J Personal Soc Psychol 89(6):852–863. https://doi.org/10.1037/0022-3514.89.6.852
134. Hayes AF (2015) An index and test of linear moderated mediation. Multivar Behav Res 50(1):1–22. https://doi.org/10.1080/00273171.2014.962683

135. Preacher KJ, Hayes AF (2008) Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behav Res Methods 40(3):879–891. https://doi.org/10.3758/brm.40.3.879
136. Fairchild AJ, MacKinnon DP (2009) A general model for testing mediation and moderation effects. Prev Sci 10(2):87–99. https://doi.org/10.1007/s11121-008-0109-6
137. Morgan-Lopez AA, MacKinnon DP (2006) Demonstration and evaluation of a method for assessing mediated moderation. Behav Res Methods 38(1):77–87. https://doi.org/10.3758/bf03192752
138. Barney J (1991) Firm resources and sustained competitive advantage. J Manag 17(1):99–120. https://doi.org/10.1177/014920639101700108
139. Grant RM (1996) Toward a knowledge-based theory of the firm. Strateg Manag J 17(S2):109–122. https://doi.org/10.1002/smj.4250171110
140. Teece DJ, Pisano G, Shuen A (1997) Dynamic capabilities and strategic management. Strateg Manag J 18(7):509–533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7%3C509::aid-smj882%3E3.0.co;2-z
141. Rindfleisch A, Malter AJ, Ganesan S, Moorman C (2008) Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. J Mark Res 45(3):261–279. https://doi.org/10.1509/jmkr.45.3.261
142. Spector PE (2019) Do not cross me: Optimizing the use of cross-sectional designs. J Bus Psychol 34(2):125–137. https://doi.org/10.1007/s10869-018-09613-8
143. Creswell JW, Creswell JD (2018) Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications. https://doi.org/10.7748/nr.12.1.82.s2
144. Guba EG, Lincoln YS (1994) Competing paradigms in qualitative research. In: Denzin NK, Lincoln YS (eds) Handbook of qualitative research. SAGE, DOI, pp 105–117. https://doi.org/10.11156/aibr.020213
145. Shadish WR, Cook TD, Campbell DT (2002) Experimental and quasi-experimental designs for generalized causal inference. Houghton Mifflin. https://doi.org/10.1086/345281
146. Bryman A, Bell E (2015) Business research methods, 4th edn. Oxford University Press, DOI. https://doi.org/10.1177/1350507608390050804
147. European Commission (2020) User guide to the SME definition. Publications Office of the European Union. https://doi.org/10.1787/9789264043466-en
148. OECD (2018) Measuring the digital transformation: A roadmap for the future. OECD Publishing. https://doi.org/10.1787/9789264302259-en
149. Mittal S, Khan MA, Romero D, Wuest T (2018) A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). J Manuf Syst 49:194–214. https://doi.org/10.1016/j.jmsy.2018.10.005
150. Barann B, Hermann A, Cordes AK, Chasin F, Becker J (2019) Supporting digital transformation in small and medium-sized enterprises: A procedure model involving publicly funded support units.

Proceedings of the 52nd Hawaii International Conference on System Sciences, 4977–4986. https://doi.org/10.24251/hicss.2019.598

151. Kline RB (2016) Principles and practice of structural equation modeling (4th ed.). Guilford Press. https://doi.org/10.1080/10705511.2023.2235083
152. Fornell C, Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. J Mark Res 18(1):39–50. https://doi.org/10.1177/002224378101800104
153. Hu LT, Bentler PM (1999) Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Struct Equ Model 6(1):1–55. https://doi.org/10.1080/10705519909540118
154. Shrout PE, Bolger N (2002) Mediation in experimental and nonexperimental studies: New procedures and recommendations. Psychol Methods 7(4):422–445. https://doi.org/10.1037/1082-989x.7.4.422
155. Aiken LS, West SG (1991) Multiple regression: Testing and interpreting interactions. SAGE, DOI. https://doi.org/10.1177/109821409301400208
156. Dawson JF (2014) Moderation in management research: What, why, when, and how. J Bus Psychol 29(1):1–19. https://doi.org/10.1007/s10869-013-9308-7
157. Kline RB (2016) Principles and practice of structural equation modeling (4th ed.). Guilford Press. https://doi.org/10.1080/10705511.2023.2235083
158. Enders CK (2010) Applied missing data analysis. Guilford Press. https://doi.org/10.1111/j.1467-842x.2012.00656.x
159. Williams LJ, Hartman N, Cavazotte F (2010) Method variance and marker variables: A review and comprehensive CFA marker technique. Organizational Res Methods 13(3):477–514. https://doi.org/10.1177/1094428110366036
160. Bagozzi RP, Yi Y (1988) On the evaluation of structural equation models. J Acad Mark Sci 16(1):74–94. https://doi.org/10.1007/bf02723327
161. Anderson JC, Gerbing DW (1988) Structural equation modeling in practice: A review and recommended two-step approach. Psychol Bull 103(3):411–423. https://doi.org/10.1037/0033-2909.103.3.411
162. Henseler J, Ringle CM, Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci 43(1):115–135. https://doi.org/10.1007/s11747-014-0403-8
163. Bharadwaj AS (2000) A resource-based perspective on information technology capability and firm performance. MIS Q 24(1):169–196. https://doi.org/10.2307/3250983
164. Wade M, Hulland J (2004) The resource-based view and information systems research. MIS Q 28(1):107–142. https://doi.org/10.2307/25148626
165. Ployhart RE, Vandenberg RJ (2010) Longitudinal research: The theory, design, and analysis of change. J Manag 36(1):94–120. https://doi.org/10.1177/0149206309352110

166. Taris TW, Kompier MA (2014) Cause and effect: Optimizing the designs of longitudinal studies in occupational health psychology. Work Stress 28(1):1–8. https://doi.org/10.1080/02678373.2014.878494
167. Shadish WR, Cook TD, Campbell DT (2002) Experimental and quasi-experimental designs for generalized causal inference. Houghton Mifflin. https://doi.org/10.1086/345281
168. Cook TD, Campbell DT, Shadish W (2002) Experimental and quasi-experimental designs for generalized causal inference. J Am Stat Assoc 97(457):341–342. https://doi.org/10.1198/jasa.2005.s22
169. Whetten DA (2009) An examination of the interface between context and theory applied to the study of Chinese organizations. Manage Organ Rev 5(1):29–55. https://doi.org/10.1111/j.1740-8784.2008.00132.x
170. Tsui AS (2007) From homogenization to pluralism: International management research in the academy and beyond. Acad Manag J 50(6):1353–1364. https://doi.org/10.5465/amj.2007.28166121
171. Lu Y, Ramamurthy K (2011) Understanding the link between information technology capability and organizational agility: An empirical examination. MIS Q 35(4):931–954. https://doi.org/10.2307/41409967
172. Tallon PP, Pinsonneault A (2011) Competing perspectives on the link between strategic information technology alignment and organizational agility: Insights from a mediation model. MIS Q 35(2):463–486. https://doi.org/10.2307/23044052
173. Jaworski BJ, Kohli AK (1993) Market orientation: Antecedents and consequences. J Mark 57(3):53–70. https://doi.org/10.1177/002224299305700304
174. Roberts N, Grover V (2012) Leveraging information technology infrastructure to facilitate a firm's customer agility and competitive activity: An empirical investigation. J Manage Inform Syst 28(4):231–270. https://doi.org/10.2753/mis0742-1222280409
175. Overby E, Bharadwaj A, Sambamurthy V (2006) Enterprise agility and the enabling role of information technology. Eur J Inform Syst 15(2):120–131. https://doi.org/10.1057/palgrave.ejis.3000600
176. Eisenhardt KM (1989) Building theories from case study research. Acad Manage Rev 14(4):532–550. https://doi.org/10.2307/258557
177. Yin RK (2018) Case study research and applications: Design and methods (6th ed.). SAGE Publications. https://doi.org/10.33524/cjar.v14i1.73
178. Gioia DA, Corley KG, Hamilton AL (2013) Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. Organizational Res Methods 16(1):15–31. https://doi.org/10.1177/1094428112452151
179. Langley A (1999) Strategies for theorizing from process data. Acad Manage Rev 24(4):691–710. https://doi.org/10.2307/259349

180. Lindsley DH, Brass DJ, Thomas JB (1995) Efficacy-performance spirals: A multilevel perspective. Acad Manage Rev 20(3):645–678. https://doi.org/10.2307/258790
181. Massey GR, Dawes PL (2007) The antecedents and consequence of functional and dysfunctional conflict between marketing managers and sales managers. Ind Mark Manage 36(8):1118–1129. https://doi.org/10.1016/j.indmarman.2006.05.017
182. Ployhart RE, Vandenberg RJ (2010) Longitudinal research: The theory, design, and analysis of change. J Manag 36(1):94–120. https://doi.org/10.1177/0149206309352110
183. Taris TW, Kompier MA (2014) Cause and effect: Optimizing the designs of longitudinal studies in occupational health psychology. Work Stress 28(1):1–8. https://doi.org/10.1080/02678373.2014.878494

Figures

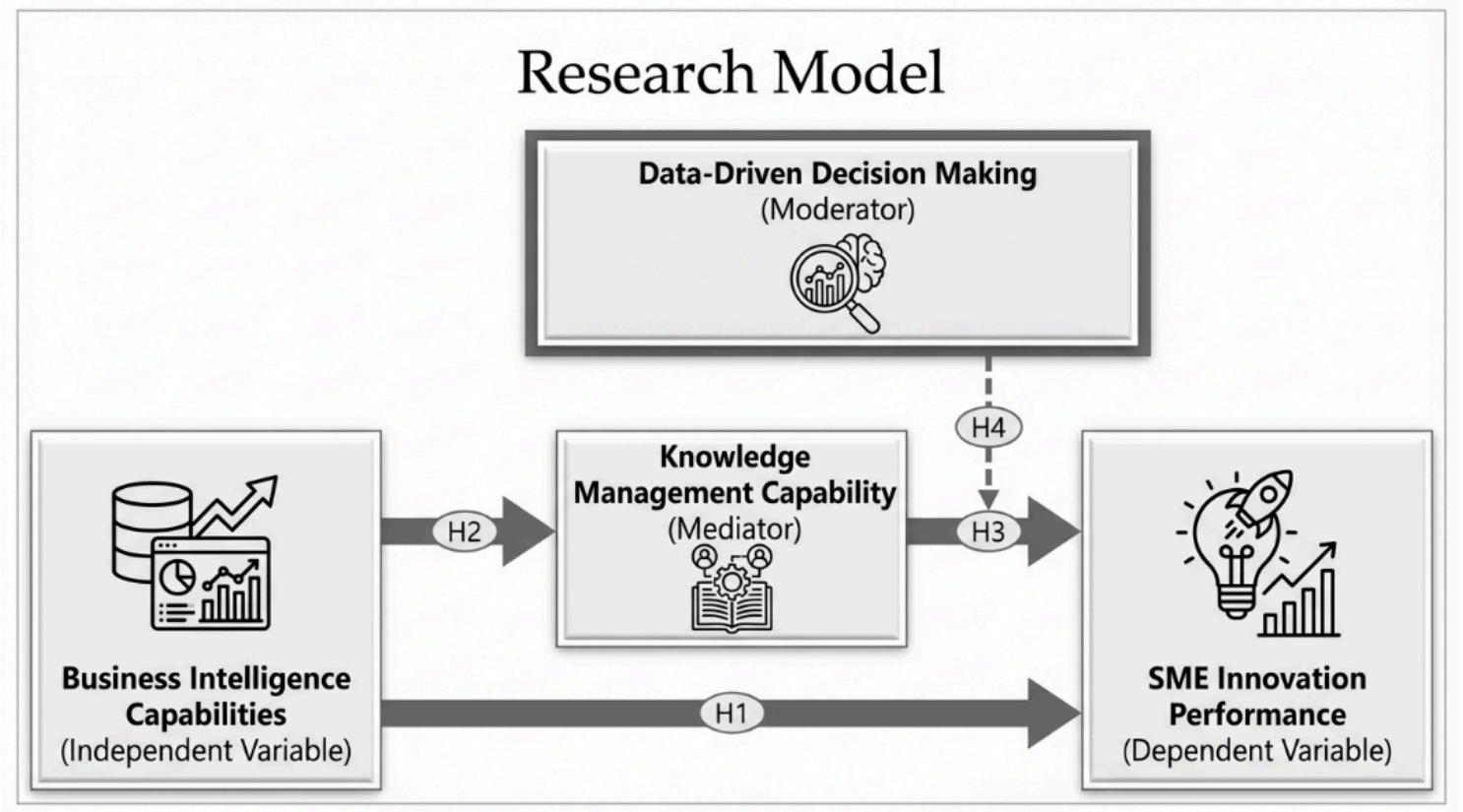


Figure 1

Conceptual Research Model

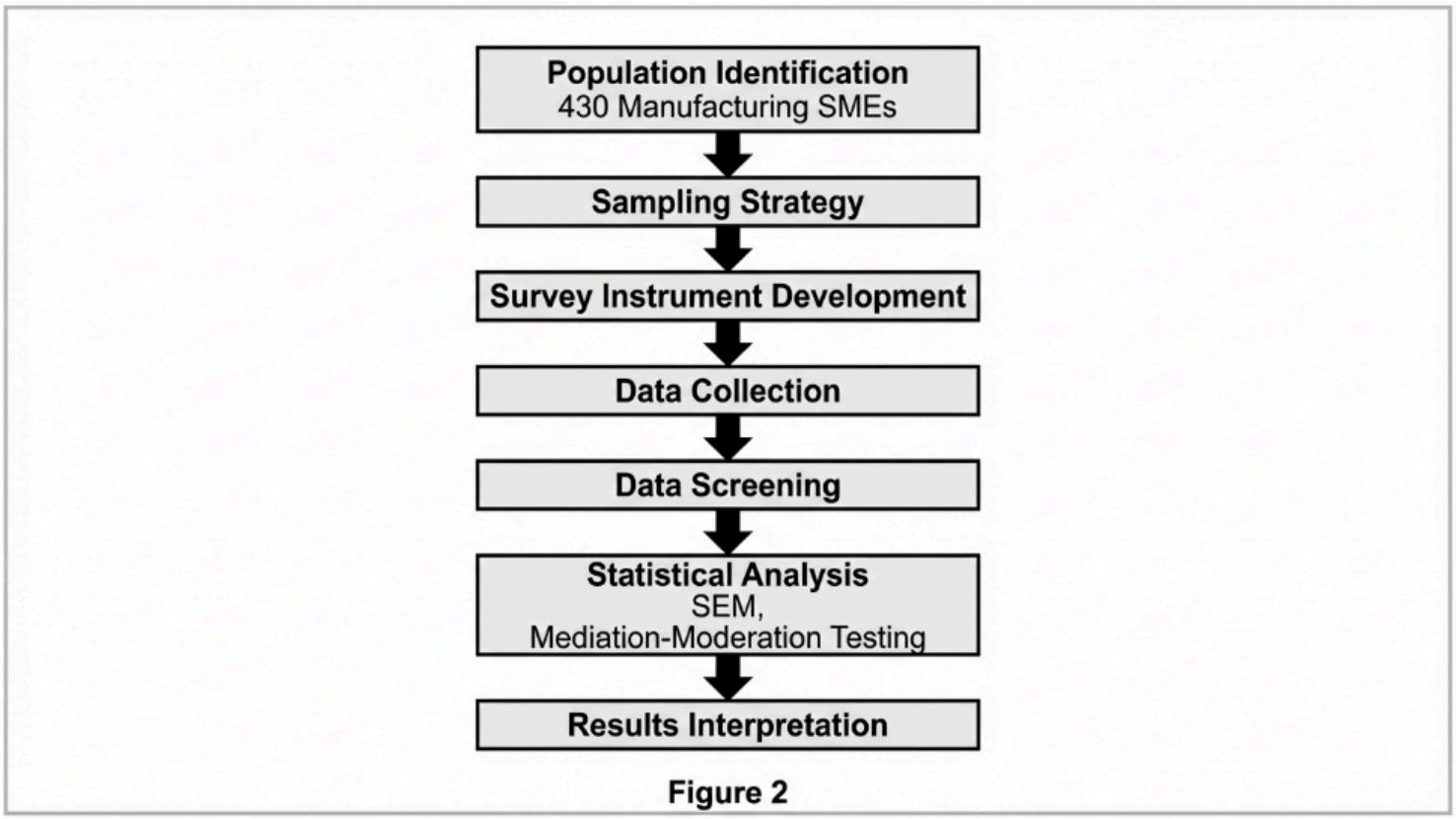


Figure 2

Structural Model Results

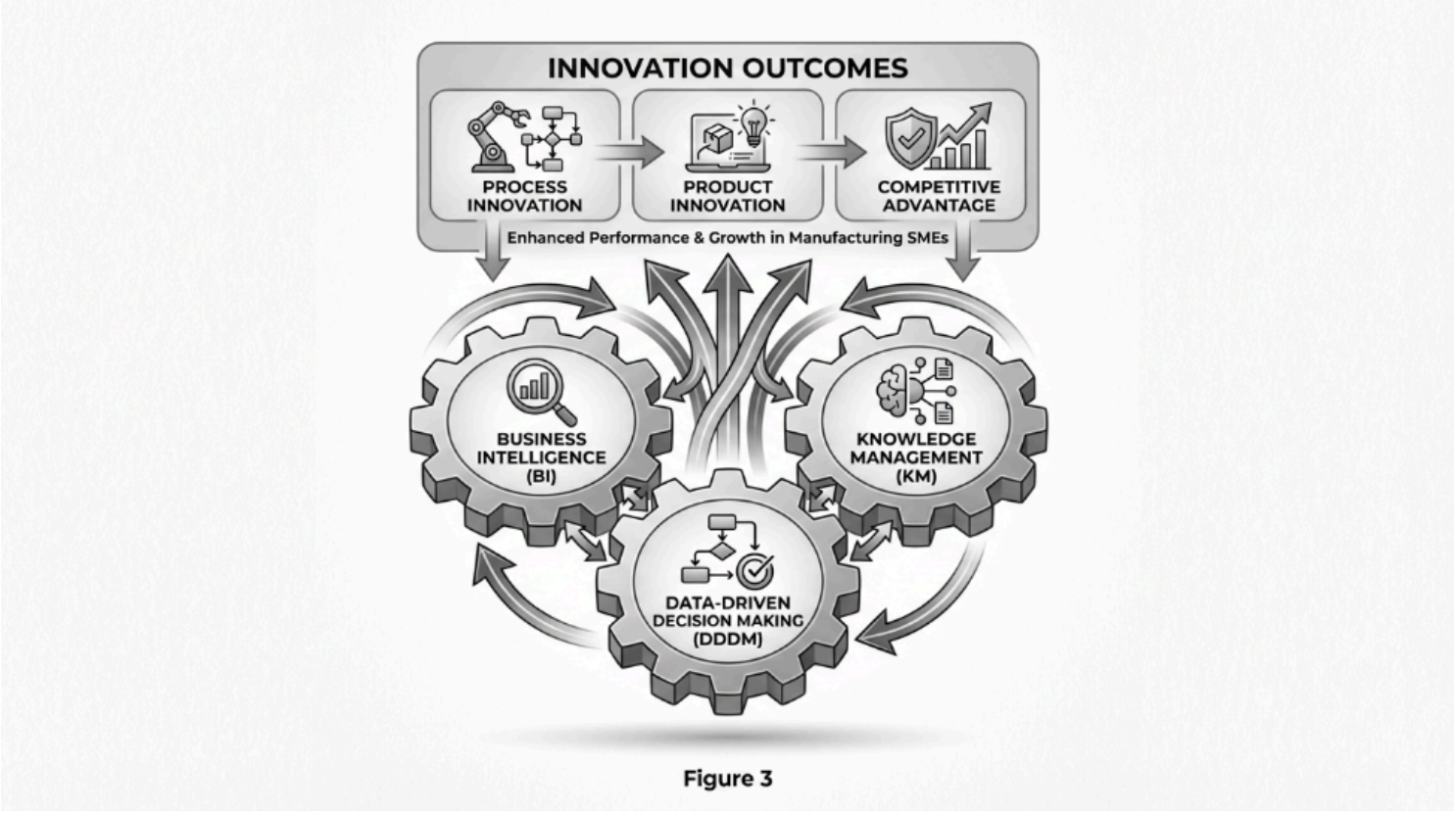


Figure 3

Interaction Effect of KM Capability and DDDM Culture on Innovation Performance

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- A.docx
- A2.docx
- D.docx
- S.docx
- Survey.docx
- V.docx