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Leveraging Knowledge Management to Drive Innovation and Technological Competence: The Moderating Role of Big Data Analytics

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Abstract

This research explores the role of Knowledge Management (KM) in enhancing technological competence and organizational innovation for sustainable organizational performance (SOP) within IT-intensive organizations in Punjab, Pakistan. A cross-sectional design was adopted, with data collected in two phases, separated by a one-month interval, using a structured, self-administered survey. The study yielded 274 usable responses from 680 participants. By drawing upon grounded theories such as the Resource-Based View (RBV), Dynamic Capabilities Theory, and the Knowledge-Based View (KBV), the research examines how KM practices, coupled with dynamic capabilities like Big Data Analytics (BDA), influence technological competence, innovation, and performance. The theoretical framework is enriched by emphasizing the role of technological competence and organizational innovation in driving sustainable performance, with BDA acting as a moderator in these relationships. Descriptive, correlation, and regression analyses were conducted using SPSS, while Structural Equation Modeling (SEM) in AMOS was utilized to test the hypothesized relationships and explore the direct and indirect effects of KM on SOP. The findings reveal that KM significantly promotes organizational innovation, with technological competence acting as a key mediator. Furthermore, BDA strengthens the effect of KM on organizational capabilities, thereby enhancing sustainable performance. This study contributes to the literature by offering new insights into how KM, BDA, and technological competence interact to foster sustained competitive advantage. By focusing on IT-intensive organizations and using a convenience sampling technique, the research highlights the critical role of KM and BDA in achieving organizational innovation and long-term performance. Future research could expand this framework to other contexts and utilize diverse sampling methods to enhance the generalizability of the findings.

Keywords: Knowledge Management (KM), Technological Competence (MC), Organizational Innovation (OI), Sustainable Organizational Performance (SOP), Big Data Analytics, Moderation and Sequential

INTRODUCTION

In today's dynamic corporate environment, organizations are facing immense pressure not only to achieve short-term financial success but also to ensure long-term sustainability and adaptability. These challenges are magnified by global economic transformations and the growing importance of knowledge-driven economies (Hock-Doepgen et al., 2021). In response, organizations are increasingly focusing on enhancing their technological competence and fostering organizational innovation as critical strategies for maintaining competitiveness. Central to these strategies is Knowledge Management (KM), which involves the systematic processes of creating, sharing, and utilizing knowledge within the organization (Zhang & Zheng, 2022). Extensive literature underscores the significance of KM in improving decision-making,

supporting innovation, and boosting technological capabilities (Bresciani et al., 2022). KM helps organizations cultivate a robust internal knowledge base that facilitates technological advancement and enhances adaptability in volatile markets. It plays a pivotal role in promoting organizational innovation, defined as the ability to generate and implement new ideas, processes, or products that contribute to competitive advantage (Azeem et al., 2021; Davoudi et al., 2018). With the advancement of digital technologies, Big Data Analytics (BDA) has emerged as a powerful complement to KM. BDA enables firms to process and analyze large, complex datasets to derive actionable insights, helping organizations to refine technological strategies and improve knowledge-sharing mechanisms (Agarwal & Dhar, 2022; Chen et al., 2023). The integration of BDA with KM provides a data-driven approach to innovation and technological development, offering organizations a significant edge in today's rapidly evolving business landscape.

This study aims to explore the relationship between KM, technological competence, and organizational innovation, emphasizing the moderating role of BDA. Technological competence refers to an organization's capacity to apply and manage technological expertise effectively. It has a direct influence on innovation capabilities and overall sustainable organizational performance (SOP). Organizations that strategically combine KM and BDA can develop dynamic capabilities that foster continuous innovation and long-term success (Mele et al., 2024). The Dynamic Capabilities Theory (DCT) offers a robust framework for understanding how firms adapt to changing environments by leveraging internal resources such as knowledge and technology. DCT highlights the ability of organizations to sense, seize, and reconfigure capabilities to maintain a competitive edge (Prayag et al., 2024). Through effective KM and BDA, organizations can enhance their dynamic capabilities and support sustainable innovation outcomes (Beigi et al., 2023).

Despite increasing interest in these themes, gaps remain in understanding the integration of KM and BDA, particularly in emerging markets where technological adoption varies due to regional and infrastructural challenges (Ghafouri-Fard et al., 2020; Akbar et al., 2024; Hussain, S. S., Ahmed, A., & Qureshi, A. R., 2024). Existing studies often focus on Western contexts, leaving the impact of KM and BDA underexplored in developing economies. This study aims to fill that gap by examining how KM and BDA influence technological competence and organizational innovation, contributing to SOP. It explores how BDA moderates the KM–innovation–competence relationship, thereby enabling organizations to optimize their strategies in the face of digital disruption and economic volatility. Moreover, it investigates how these factors align with DCT to foster resilience, adaptability, and strategic renewal in a data-driven era (Hong, 2012; Tran et al., 2022). The study also contributes to theoretical advancement by integrating KM, BDA, and DCT in a unified framework. It provides empirical insights into how organizations can leverage these elements to improve innovation processes and maintain sustainable performance (Garrido-Moreno et al., 2024; Bougoulia & Glykas, 2023). In addition, it acknowledges the role of cultural and economic variations in shaping KM practices across different geographical contexts (Malik et al., 2023; Steinmueller, 2002).

By doing so, this research offers practical guidance for managers and policymakers on implementing integrated KM and BDA strategies to build technological competence, foster innovation, and enhance sustainable performance. It further illustrates the significance of dynamic capabilities in achieving a sustained

competitive advantage amid the challenges of globalization and digital transformation (Malhotra, 2004; Pai et al., 2022).

LITERATURE REVIEW

This literature review examines the key concepts of Knowledge Management (KM), Technological Competence (TC), Organizational Innovation (OI), and Big Data Analytics (BDA) and their interrelationships, focusing on the role these constructs play in enhancing organizational performance and competitiveness. The chapter provides an in-depth exploration of the relevant theories, empirical findings, and the research gaps in these areas. Additionally, the review presents a conceptual framework for understanding how these elements interact and contribute to sustainable organizational performance (SOP).

Knowledge Management (KM)

Knowledge Management (KM) is defined as the systematic process of managing and leveraging organizational knowledge to improve performance, foster innovation, and sustain competitive advantage. It involves acquiring, sharing, and utilizing knowledge within an organization (Nonaka & Takeuchi, 1995). According to Davenport and Prusak (1998), KM enables organizations to leverage their intellectual assets by creating a knowledge-sharing culture, which enhances problem-solving and decision-making processes. Research has demonstrated that KM can lead to improved organizational performance, increased productivity, and innovation by enabling better coordination and resource allocation (Farrukh *et al*., 2022). KM is closely tied to organizational competencies, which are defined as the skills, capabilities, and knowledge required to perform business activities effectively. These competencies play a critical role in shaping an organization's ability to innovate and respond to changing market conditions. Research by Teece *et al*. (2016) emphasizes that KM contributes to dynamic capabilities that are skills that help organizations adapt and reconfigure their resources to achieve long-term success. Additionally, effective KM systems can facilitate the development of absorptive capacity, which refers to the ability to recognize, assimilate, and apply new knowledge (Cohen & Levinthal, 1990).

Technological Competence (TC) and Organizational Innovation (OI)

Technological Competence (TC) refers to an organization's ability to develop, integrate, and apply advanced technologies to meet business objectives. The importance of technological competence has increased in the digital age as firm's leverage technological innovations to improve productivity, reduce costs, and enhance customer experiences (Turi *et al*., 2023). Technological competence is often developed through investments in R&D, technological infrastructure, and the training of employees to handle emerging technologies (Zahra & George, 2002). Organizational Innovation (OI) involves the creation, development, and application of new ideas, products, processes, or business models that lead to competitive advantage and organizational growth. Research highlights that technological competence is a key enabler of organizational innovation (Teece, 2007). It is through technological competence that organizations can enhance their innovation processes, improve efficiency, and differentiate themselves in competitive markets (Teece *et al*., 2016). As a result, organizations that invest in technological capabilities are better positioned to drive innovation and achieve sustainable competitive advantage. Scholars have shown that KM and technological competence are

deeply intertwined, with KM facilitating the acquisition and dissemination of technological knowledge necessary for innovation (Turi *et al*., 2023). Knowledge-sharing practices enhance the dissemination of technological know-how, leading to the creation of new ideas and solutions. Moreover, organizations with strong KM systems are better equipped to harness their technological capabilities and translate them into innovative products and services (Zahra & George, 2002).

Big Data Analytics (BDA) as a Moderating Factor

Big Data Analytics (BDA) refers to the process of examining large and complex datasets; both structured and unstructured to uncover hidden patterns, correlations, and insights that can inform business decision-making. The integration of BDA into organizational processes has been shown to enhance data-driven decision-making and improve organizational outcomes (Akbar *et al*., 2024). BDA enables organizations to analyze vast amounts of data in real-time, which helps in identifying market trends, customer preferences, and operational inefficiencies (Fosso Wamba *et al*., 2024). As a result, firms that incorporate BDA into their KM systems can derive actionable insights that improve organizational performance, enhance innovation, and foster competitive advantage (Ferraris *et al*., 2019).

The moderating role of BDA in the relationship between KM and organizational performance is increasingly recognized in recent studies. BDA helps organizations manage vast amounts of knowledge and data, making it easier to identify valuable insights, optimize operations, and predict future trends (Alzghoul *et al*., 2024). For example, BDA can facilitate the analysis of customer feedback and market data, enabling organizations to align their KM strategies with customer needs and market demands. As a result, BDA can strengthen the impact of KM on organizational innovation and technological competence, contributing to sustainable organizational performance (Akbar *et al*., 2024).

Linking KM, Technological Competence, Innovation, and BDA to Sustainable Organizational Performance

The concept of Sustainable Organizational Performance (SOP) refers to an organization's ability to achieve long-term success through the effective use of its resources, including knowledge, technology, and human capital. SOP is driven by the organization's capacity to innovate, adapt to changes, and remain competitive in the marketplace. The literature suggests that the combination of KM, technological competence, and innovation is critical to achieving SOP (Choudri *et al*., 2016). Research by Hock-Doepgen *et al*. (2021) shows that organizations that integrate these elements into their operations are better positioned to achieve sustainable growth and profitability in a volatile business environment.

KM and technological competence directly contribute to organizational innovation, which is a key driver of SOP. By managing knowledge resources effectively, organizations can foster a culture of innovation that leads to the development of new products, services, and business models (Turi *et al*., 2023). Furthermore, technological competence enables organizations to apply advanced technologies to improve efficiency, reduce costs, and create new value propositions. BDA plays a moderating role in this process by providing organizations with insights derived from large datasets that inform decision-making and guide innovation (Farrukh *et al*., 2022). This integration of knowledge and data-driven technologies enables organizations to stay

ahead of competitors, enhance customer satisfaction, and achieve sustainable performance.

Theoretical Framework and Hypotheses Development

This study investigates the relationship between Knowledge Management (KM), Technological Competence (TC), Organizational Innovation (OI), and Sustainable Organizational Performance (SOP), with a focus on how Big Data Analytics (BDA) moderates these interactions. KM, as an independent variable, influences SOP through knowledge utilization and sustainability (Arduini *et al*., 2023). Prior research indicates that technological competence (TC) enhances the impact of KM on SOP (Beyer *et al*., 2011; Andersson *et al*., 2015). Organizational innovation is identified as a critical mediator in the KM-SOP relationship (Hutomo *et al*., 2018), while BDA is seen as a key moderator that strengthens the connections between KM, TC, and MC, thereby contributing to sustainable performance (Salloum *et al*., 2017).

The study argues that traditional KM systems are insufficient in today's data-driven business environment. Emerging technologies like BDA, blockchain, and artificial intelligence are necessary to enhance KM systems for better decision-making and innovation (Mhamdi *et al*., 2018; Ferraris *et al*., 2019). BDA, in particular, helps organizations efficiently capture, analyze, and apply knowledge, fostering innovation and competitive advantage (Boyd & Crawford, 2012; Cao *et al*., 2015). Research shows that BDA strengthens the relationship between KM and organizational capabilities, helping overcome inertia and improving knowledge utilization (Mikalef *et al*., 2021; Dahiya *et al*., 2021). This study hypothesizes that BDA moderates the relationships between KM and both TC and MC, enhancing their impact on SOP (Singh & El-Kassar, 2018; Lozada *et al*., 2023). By facilitating data-driven insights, BDA enables better decision-making, innovation, and long-term organizational growth (Hayaeian *et al*., 2021; Ju *et al*., 2022). The integration of BDA with KM is critical for improving organizational performance and sustaining innovation in a digitalized environment.

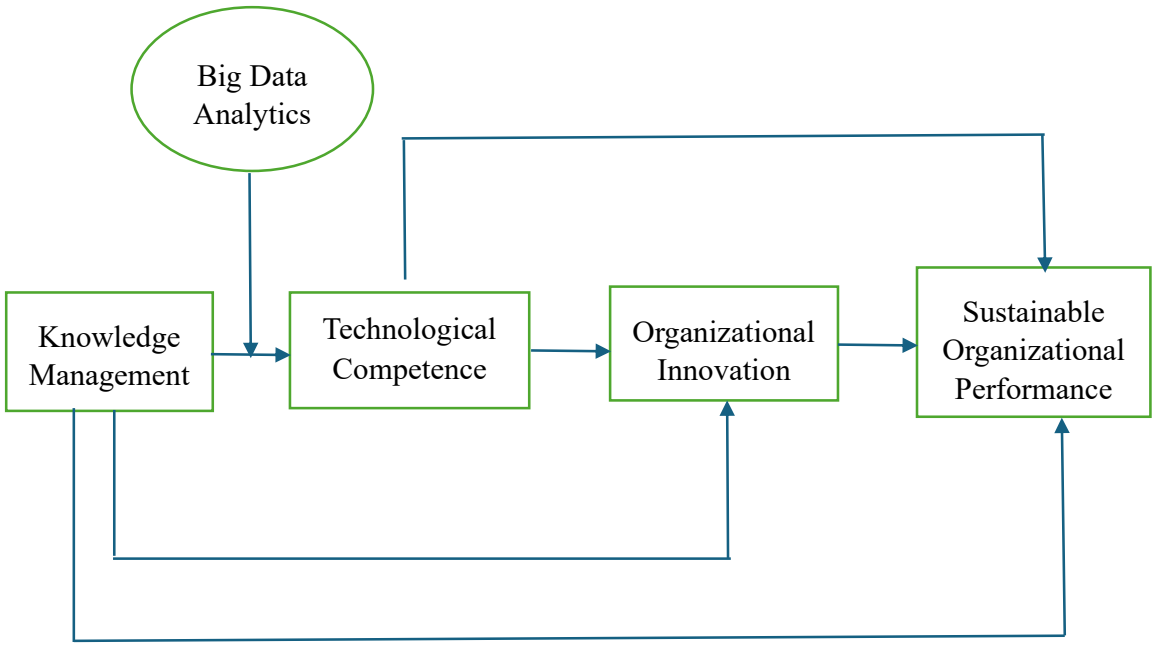
The theoretical foundations for this study include the Resource-Based View (RBV), Knowledge-Based View (KBV), Social Exchange Theory (SET), and Dynamic Capabilities Theory (Teece *et al*., 2016). These perspectives highlight how organizations can develop dynamic capabilities to adapt to changing environments and maintain competitive advantages. The study emphasizes that marketing and technological competences, as key capabilities, drive innovation and sustainable performance (Khan *et al*., 2022; Manesh *et al*., 2021). Integrating these competences through KM is essential for fostering innovation and achieving SOP (Al-Khatib, 2022; Mikalef *et al*., 2021).In sum, this study proposes an integrated framework that links KM, innovation, organizational capabilities, and advanced technologies to SOP. It underscores the moderating role of BDA in enhancing the effectiveness of KM and organizational competences, providing insights into how technology-driven innovation can improve organizational performance and competitiveness in a rapidly evolving business landscape.

DEVELOPING HYPOTHESES

The present study explores how Knowledge Management (KM), Technological Competence (TC), Organizational Innovation (OI), and Big Data Analytics (BDA) collectively contribute to Sustainable Organizational Performance (SOP). Drawing from theoretical perspectives such as the Knowledge-Based View (KBV) and Dynamic

Capabilities Theory (DCT), the study formulates eight hypotheses to investigate both direct and indirect relationships among these constructs. KM is proposed as a central capability that drives SOP both directly and indirectly through TC and OI.

Figure 1.
Conceptual Framework



TC is examined not only as an outcome of KM but also as a precursor to innovation. OI, in turn, is posited to positively influence SOP and mediate key relationships in the model. The moderating effect of BDA is also tested to determine whether it strengthens the impact of KM on TC. Moreover, sequential mediation through TC and OI is proposed as a comprehensive pathway through which KM enhances SOP. The hypotheses are presented as follows:

H_1: KM positively influences sustainable organizational performance (SOP).

H_2: KM positively influences technological competence (TC).

H_3: Technological competence (TC) positively impacts organizational innovation (OI).

H_4: Organizational innovation (OI) positively influences sustainable organizational performance (SOP).

H_5: BDA moderates the relationship between KM and TC.

H_6: TC mediates the relationship between KM and OI.

H_7: OI mediates the relationship between TC and SOP.

H_8: TC and OI sequentially mediate the relationship between KM and SOP.

DATA ANALYSIS AND RESULTS

This section outlines the data analysis process used to test the research hypotheses concerning the impact of Knowledge Management (KM) on technological competence and organizational innovation, with Big Data Analytics (BDA) as a moderator. This section begins with data preparation steps, including screening,

coding, normality checks, handling missing values, identifying outliers, and summarizing respondent demographics. Descriptive and correlational statistics provide an initial overview, while construct reliability is assessed to ensure measurement consistency. Structural Equation Modeling (SEM) is employed to test the hypothesized relationships, allowing for analysis of both direct and indirect effects, including mediation and moderation. Moderation is tested using the bootstrapping approach (Iacobucci et al., 2007) and Baron and Kenny's (1986) method. Data analysis is conducted using AMOS 23.0 for SEM and SPSS 23.0 for descriptive and inferential statistics (Byrne, 2016; Field, 2013). AMOS supports complex model testing, while SPSS aids in regression and other statistical procedures. The combined use of these tools strengthens the analytical rigor and provides a comprehensive understanding of how KM, BDA, technological competence, and innovation interact (Kline, 2015).

Demographics

In this survey, four key demographic dimensions were considered: gender, age, education, and work experience. A total of 274 respondents from selected IT-based companies and software houses participated in the study by completing self-administered questionnaires.

Gender: Respondents were categorized as 1=male and 2=female. The majority, 63% (n=173), were male, while 37% (n=101) were female.

Age: Respondents were grouped into four age brackets. The largest group was 30-39 years old, with 36% (n=99) of respondents. The second-largest group was 20-29 years old, comprising 27% (n=74). The third group was 40-49 years old, accounting for 31% (n=85), and the smallest group was 50-60 years old, making up 6% (n=16).

Education: Education levels were categorized as follows: 1=Intermediate/ADP (12-14 years), 2=Undergraduate (16 years), and 3=Masters and above (18 years and above). In this survey, 13% (n=36) of respondents had Intermediate-level education, 61% (n=167) had an undergraduate degree, and 26% (n=71) held a Master's degree or higher.

Experience: Respondents' job experience was categorized into three brackets: 1=1-5 years, 2=6-10 years, and 3=11 years and above. The largest group, 43% (n=118), had 6-10 years of experience. 37% (n=101) had 1-5 years of experience, and 20% (n=55) had over 10 years of experience.

Table 1.
Demographics

Demographics	Dimension	Frequency	Percentage (%)
Gender	Male	173	63%
	Female	101	37%
Age	20-29 Years	74	27%
	30-39 Years	99	36%
	40-49 Years	85	31%
	50-60 Years	16	6%
Education	Intermediate/ADP (12-14 years)	36	13%
	Undergraduate (16 years)	167	61%
	Graduate/Masters and above (18 years and above)	71	26%
Experience	1-5 Years	101	37%
	6-10 Years	118	43%
	11 Years or above	55	20%

Descriptive Statistics

Descriptive statistics play a critical role in this study by summarizing and understanding the key characteristics of the sample population. As noted by Bickel and Lehman (1975), these statistics provide valuable insights into the central tendencies and variability of the data, which are essential for examining the relationships between Knowledge Management (KM) practices and Sustainable Organizational Performance (SOP). Descriptive measures, such as means and medians, highlight the central location of the data, while standard deviations and inter-quartile ranges help assess the spread and variability of the data points. Sekaran (2000) highlighted that frequency and percentage distributions are particularly useful for summarizing categorical data. In this study, variables such as Sustainable Organizational Performance (SOP), Knowledge Management (KM), Big Data Analytics (BDA), Organizational Innovation (OI), and Technological Competence (TC) are analyzed to identify patterns and relationships. This analysis provides deeper insights into how KM practices, enhanced by Big Data Analytics (BDA), influence organizational performance outcomes (Ferreira & Oliveira, 2014).

In addition, the study calculates the mean and standard deviation to offer a comprehensive overview of the demographic characteristics of the sample population, including gender, age, education, and job experience. These demographic variables are important for understanding the diversity of the sample and assessing how they may impact the relationships between KM, BDA, TC, OI, and SOP. The table 3.2 below presents the mean and standard deviation for each of these variables.

Table 2.
Descriptive Statistics

No.	Variables	Mean	SD
1	Sustainable Organizational Performance	3.30	0.85
2	Organizational Innovation	3.38	0.85
3	Technological Competence	3.20	0.91
4	Big Data Analytics	3.40	0.90
5	Knowledge Management	3.26	0.94

Reliability

To ensure the reliability and internal consistency of the measurement instrument, Cronbach's alpha values were calculated for the five key variables: Knowledge Management (KM), Big Data Analytics (BDA), Technological Competence (TC), Organizational Innovation (OI), and Sustainable Organizational Performance (SOP). Following Nunnally and Bernstein's (1994) threshold of 0.70, all constructs demonstrated acceptable internal consistency. A pretest with 25 respondents assessed the clarity and relevance of questionnaire items (Brislin, 1980), and Cronbach's alpha results (Table 3.3) confirmed strong reliability. These findings validate the instrument's suitability for accurately measuring the study variables (Field, 2013).

Table 3.
Construct Reliability

Variables	No. of Items	Cronbach's Alpha
Sustainable Organizational Performance	6	0.87
Organizational Innovation	8	0.90
Technological	4	0.81

Competence		
Big Data Analytics	12	0.91
Knowledge Management	5	0.84

Correlation Analysis

Correlation analysis is used to assess the strength and direction of the linear relationships between variables. McMillan (1993) suggests that correlation values can be interpreted as follows: a value between 0.1 and 0.3 indicates a weak relationship, between 0.3 and 0.7 suggests a moderate relationship, and values above 0.7 (>0.7) indicate a strong relationship. Additionally, the p-value is used to test the significance of these relationships. A p-value less than 0.05 ($p < 0.05$) signifies a statistically significant relationship. In this section, bivariate Pearson correlation (r) coefficients and their corresponding p-values for all variables in the study are calculated. Participants from IT-based companies and software houses were asked to complete a Likert scale survey ranging from 1 to 5, indicating the extent to which they agreed or disagreed with statements concerning Knowledge Management (KM), Big Data Analytics (BDA), Technological Competence (TC), Organizational Innovation (OI), and Sustainable Organizational Performance (SOP).

These variables are critical in understanding how organizations can utilize KM practices and emerging technologies to enhance their long-term performance. The statistical analysis of the data shows the existence of correlation between all linear relationships of the study variables. For instance, SOP is correlated with OI ($r = 0.309$, $p \leq 0.01$), TC ($r = 0.313$, $p \leq 0.01$), BDA ($r = 0.157$, $p \leq 0.01$) and KM ($r = 0.321$, $p \leq 0.01$). Similarly, OI is correlated with TC ($r = 0.306$, $p \leq 0.01$), BDA ($r = 0.205$, $p \leq 0.01$) and KM ($r = 0.239$, $p \leq 0.01$). Moreover, TC has an association with BDA ($r = 0.245$, $p \leq 0.01$) and KM ($r = 0.448$, $p \leq 0.01$). Likewise, the BDA has an affiliation with KM ($r = 0.321$, $p \leq 0.01$). Table 3.4 demonstrates the correlation analysis.

Table 4.
Correlation Analysis

Variables	Mean	SD	1	2	3	4	5
Sustainable Organizational Performance	3.30	0.85	(0.87)				
Organizational Innovation	3.38	0.85	0.309**	(0.90)			
Technological Competence	3.20	0.91	0.313**	0.306**	(0.81)		
Big Data Analytics	3.40	0.90	0.157**	0.205**	0.245**	(0.91)	
Knowledge Management	3.26	0.94	0.321**	0.293**	0.448**	0.321**	(0.84)

** $p \leq 0.01$, *. $p \leq 0.05$.

Parentheses forming diagonal represent Cronbach's alpha (α).

Validity

Construct validity refers to how well a measurement tool captures the theoretical concept it intends to assess (Cronbach & Meehl, 1955). To establish this, the study employed both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). EFA was used to uncover the underlying dimensions of the five key constructs—KM, BDA, TC, OI, and SOP—while CFA validated the factor structure and confirmed that the measurement items aligned with the theoretical model, supported by strong factor loadings and fit indices (Hair et al., 2010; Bagozzi & Yi, 1988).

Exploratory Factor Analysis (EFA)

EFA helped identify the factor structure of the observed variables without a predefined framework (Hair et al., 2010). It ensured that the questionnaire items

loaded appropriately on their respective constructs, with loadings above the recommended threshold of 0.40 (Tabachnick & Fidell, 2013). In this study, all five latent variables showed strong factor loadings above 0.50, except for four BDA items (BDA4, BDA8, BDA9, BDA10), which were removed due to low loadings below 0.40. Eliminating these items improved the instrument's reliability and refined the measurement model (Field, 2013). Full results are presented in Table 3.5.

Confirmatory Factor Analysis (CFA)

CFA was conducted to validate the measurement model and assess how well the observed data fit the hypothesized structure (Hair et al., 2010; Byrne, 2010). The model demonstrated good fit (χ^2 = 1220.715, df = 687, χ^2/df = 1.777, RMSEA = 0.050, CFI = 0.91, NNFI = 0.907), meeting recommended thresholds (Hu & Bentler, 1999; Cheung & Rensvold, 2002). In contrast, the one-factor model performed poorly, confirming the superiority of the six-factor structure. To ensure robustness, several alternative models were tested by combining different constructs, but all showed inferior fit compared to the proposed model. These findings confirm the distinctiveness and validity of the five constructs used in this study.

Table 5.
Confirmatory Factor Analysis

Variables	χ^2	d.f	Ratio χ^2 / d.f	CFI	NNFI	RMSEA
5-factor model[a]	1220.715	687	1.777	0.914	0.907	0.050
4-factor model[b]	1808.130	692	2.613	0.821	0.808	0.072
3-factor model[c]	2466.485	696	3.544	0.715	0.697	0.090
2-factor model[d]	2763.617	699	3.954	0.668	0.648	0.097
1-factor model[e]	3460.116	701	4.936	0.556	0.531	0.112

5-factor model meets the criteria of suggested standard numbers (χ2/df < 3, while RMSEA < 0.08, CFI ≥ 0.90, NNFI ≥ 0.90) *(Hu and Bentler, 1999)*.

Factor Loadings

Factor loadings reflect the strength of the relationship between observed variables and their underlying constructs in CFA. Loadings above 0.40 are generally acceptable, indicating strong predictive power (Hair et al., 2010; Schumacker & Lomax, 2016). In this study, all items for KM, BDA, TC, OI, and SOP showed loadings above 0.50, confirming that the items reliably represent their respective constructs. Detailed results are shown in Table 3.6.

Convergent and Discriminant Validity

The measurement model's reliability and validity were assessed using Cronbach's alpha and Composite Reliability (CR), with values >0.70 indicating strong internal consistency (Hair et al., 2017). Convergent validity was confirmed through AVE values >0.50 (Fornell & Larcker, 1981), and discriminant validity was assessed via HTMT and the Fornell-Larcker criterion (Henseler et al., 2015). Each construct's MSV was below 0.50 and less than its AVE, affirming discriminant validity. Goodness-of-fit indices (CFI, RMSEA, NFI) also supported model adequacy (Hu & Bentler, 1999). Full results are presented in Table 4.9.

1. The values in diagonal are the square root of AVE

2. TC – Technological Competence, KM – Knowledge Management, OI – Organizational Innovation, SOP

– Sustainable Organizational Performance and BDA – Big Data Analytics

3. Correlation is significant at 0.01 level (2-tailed)

Table 6.
Convergent and Discriminant Validity

	CR	AVE	MSV	1	2	3	4	5
SOP	.87	.53	.149	**(.73)**				
OI	.90	.54	.167	.252	**(.73)**			
TC	.81	.52	.243	.386	.344	**(.73)**		
BDA	.91	.56	.169	0.310	.375	.371	**(.75)**	
KM	.84	.51	.243	.319	.324	.493	.337	**(.71)**

Common Method Bias

To reduce common method bias, the study used both qualitative and quantitative methods and adopted a time-lagged, multi-wave survey design (Podsakoff et al., 2012). Data were collected in two phases: Phase 1 (T1) gathered KM and demographic data, while Phase 2 (T2), conducted a month later, focused on technological competence, organizational innovation, BDA, and sustainable performance. Harman's single-factor test (Podsakoff et al., 2003) was applied to assess bias. The single factor accounted for only 22.23% of the variance which is well below the 50% threshold (Mattila & Enz, 2002), indicating that common method bias was not a major concern.

Path Analysis

Path analysis, within the SEM framework, examines both direct and indirect relationships between variables (Kline, 2016; MacKinnon, 2008). It is especially useful for testing theoretical models with linear causal structures (Schumacker & Lomax, 2016; Hair et al., 2021). In this study, four direct paths were tested: KM → SOP, KM → TC, TC → OI, and OI → SOP. All hypotheses were supported, with significant positive relationships confirmed (Table 3.7).

Table 7.

Direct Path Analysis

Hypothesis	Results	Estimate	Lower	Upper	P-Value
H_1	KM→ SOP	.351	.205	.459	.028
H_2	KM→ TC	.574	.430	.706	.020
H_3	TC→ OI	.400	.259	.508	.016
H_4	OI→ SOP	.296	.196	.383	.012

Estimate based on 10,000 bootstraps with *95% confidence interval*

SOP: Sustainable Organizational Performance// OI: Organizational Innovation//TC: Technological Competence // KM: Knowledge Management

Indirect Path Analysis

The results presented in Table 3.8 confirm that all four indirect relationships are positive, indicating that in each case, the indirect effect (mediated through OI) positively contributes to the outcome (SOP). This suggests that the mediation effect of OI strengthens the relationship between the initial factors (KM, TC) and SOP. The positive direction of these relationships implies that knowledge management and technological competence, when combined with organizational innovation, significantly enhance sustainable performance within organizations. Therefore, the

findings support the notion that Organizational Innovation (OI) acts as a key mediator, amplifying the positive impact of KM and TC on Sustainable Organizational Performance (SOP).

Table 8.
Indirect Path Analysis

Hypothesis	Results	Estimate	Lower	Upper	P-Value	Conclusion
H_6	KM→OI	.233	.067	.439	.007	Partial
	KM→TC→OI	.163	.075	.251	.018	Médiation
H_7	TC→ SOP	.276	.173	.407	.006	Partial
	TC→OI→ SOP	.082	.042	.143	.008	Médiation

Estimate based on 10,000 bootstrap with *95% confidence interval*

SOP: Sustainable Organizational Performance// OI: Organizational Innovation//TC: Technological Competence // KM: Knowledge Management

Sequential Mediation Analysis

The results presented in Table 3.9 confirm that both the indirect relationships are positive, indicating that the indirect effect mediated through Organizational Innovation (OI) contributes positively to the outcome of Sustainable Organizational Performance (SOP). This suggests that OI plays a key role in strengthening the connection between Knowledge Management (KM), Technological Competence (TC), and SOP. The positive nature of these relationships highlight the significant impact that combining KM and TC with OI have on improving sustainable performance within organizations. Therefore, the findings underscore the importance of OI as a critical mediator, enhancing the positive influence of KM and TC on SOP.

Table 9.
Sequential Mediation Analysis

Hypothesis	Results	Estimate	Lower	Upper	P-Value	Conclusion
H_8	KM→TC→OI→ SOP	.057	.029	.088	.013	Partial Médiation

Estimate based on 10,000 bootstrap with *95% confidence interval*

SOP: Sustainable Organizational Performance// OI: Organizational Innovation //TC: Technological // KM: Knowledge Management

Moderation Analysis

The moderation analysis shown in Table 3.10 for testing H_8 reveals a statistically significant interaction between Big Data Analytics (BDA) and Knowledge Management (KM) in influencing Technological Competence (TC). The beta value of 0.109 indicates a positive moderation effect, suggesting that as BDA increases, the strength of the relationship between KM and TC becomes stronger. This implies that BDA enhances the impact of KM on TC, although the effect size is moderate rather than large.

The t-value of 2.191 further supports the significance of this moderation effect, as it exceeds the threshold of 2.0, indicating that the interaction term is statistically meaningful. With a p-value of 0.02, we can confidently conclude that the moderation effect is significant, emphasizing the importance of BDA in strengthening the relationship between KM and TC. In summary, BDA positively moderates the relationship between KM and TC with a small but meaningful effect. The results suggest that BDA amplifies the impact of KM on TC, and this effect is statistically significant.

Table 10.
Moderation Analysis

Hypothesis	Path	B	t-value	P
H_5	KM→ TC	.422	8.067	.000
	BDA→ TC	.159	2.947	.003
	KM*BDA→ TC	.109	2.191	.02

Estimate based on 10,000 bootstraps with *95% confidence interval*

SOP: Sustainable Organizational Performance// TC: Technological Competence // KM: Knowledge Management

Figure-1 illustrates the results for H_5, where BDA moderates the relationship between KM and TC. The graph highlights the interaction effect of BDA on this relationship. With a beta value of 0.109, a t-value of 2.191, and a p-value of 0.02, the moderation effect is statistically significant. The graph also reveals that at higher levels of BDA, the relationship between KM and TC strengthens, indicating a positive moderation. The line representing the relationship between KM and TC shows a steeper incline at higher levels of BDA compared to when BDA is low, signifying that BDA enhances the impact of KM on TC.

Figure2.

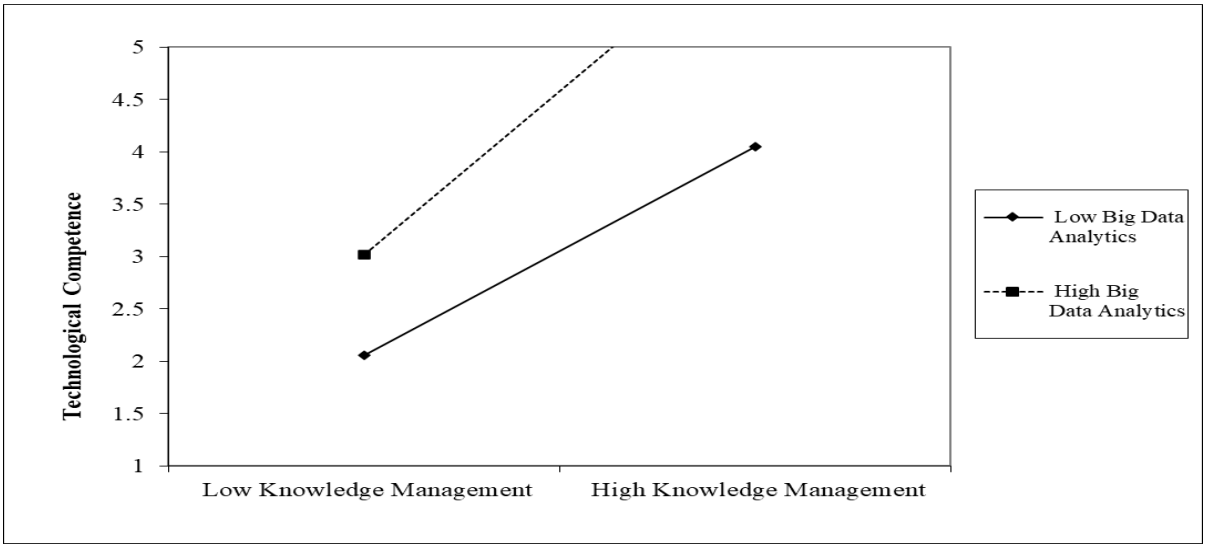


Illustration of the moderating effect of big data analysis on the relationship between knowledge management and technological competence.

Table 11.
Results Summary of the Study

Hypothesis	Relationship	Accepted (Yes / No)
H_1	KM has positive relationship with sustainable organizational performance (SOP)	Yes
H_2	KM has positive relationship with technological competence (TC)	Yes
H_3	Technological competence (TC) has positive impact on organizational innovation (OI)	Yes
H_4	Organizational innovation (OI) has positive relationship with sustainable organizational performance (SOP)	Yes
H_5	Big data analytics moderates the relationship between knowledge management (KM) and Technological Competence (TC)	Yes

H_6	There a is significant mediation effect of Technological Competence (TC) between the relationship of knowledge management (KM) and Organizational Innovation (OI)	Yes
H_7	There is a positive mediation effect of Organizational Innovation (OI) between Technological Competence (TC) and Sustainable Organizational Performance (SOP)	Yes
H_8	There is a sequential mediation of Technological Competence (TC) and Organizational Innovation (OI) between KM and SOP	Yes

DISCUSSIONS AND RESEARCH IMPLICATIONS

In this section, the key findings of the study, derived from the research objectives, are presented and compared with existing empirical evidence. It also discusses the interpretations of the results, along with their theoretical and practical implications. Additionally, the limitations of the study and potential avenues for future research are outlined, followed by a final conclusion. To achieve the study's objectives, eight hypotheses were formulated to examine the relationships between key variables. This section provides a detailed discussion of the results for each hypothesis, supported by evidence from existing literature and statistical data, offering insights into how these variables interact and contribute to the research questions.

Direct Relationships

The first objective of the study was "*to explore the impact of knowledge management (KM) on sustainable organizational performance (SOP) through the development of organizational competencies, including technological and organizational innovation*." To address this, four hypotheses (H_1 to H_4) were tested. The study's findings confirmed all four hypotheses as positive, with the results strongly supported by existing literature. The direct relationships (H_1 to H_4) and their interpretations are presented in Section-3, Table 3.7.

H_1. KM has a positive relationship with SOP

The relationship between KM and SOP has been extensively discussed in the literature, with KM recognized as a key driver for long-term organizational success. KM practices, such as efficient knowledge capture, sharing, and application, enhance innovation, decision-making, and resource optimization, all contributing to sustainable performance (Alavi & Leidner, 2021). Effective KM, including knowledge sharing and organizational learning, helps organizations adapt to changing environments, improve operational efficiency, and foster innovation, thus supporting sustainability (Junni *et al*., 2020). Moreover, aligning KM with sustainability goals creates a competitive advantage by integrating knowledge with environmental and social responsibility initiatives (Cohen & Levinthal, 2022). This study confirms the positive relationship between KM and SOP, aligning with prior research and highlighting KM's role in achieving long-term sustainable organizational performance.

H_2. KM has positive relationship with technological competence (TC)

The extent literature expounds that the relationship between Knowledge Management (KM) and technological competence has been well-documented in the literature, with KM practices playing a pivotal role in enhancing an organization's technological capabilities. Effective KM systems facilitate the acquisition, sharing and application of technological knowledge which helps organizations stay competitive by improving their technological expertise and innovation (Grant, 2021). By fostering knowledge sharing and collaboration, KM enables employees to better utilize existing technologies and adapt to new technological advancements (Zhang *et al*., 2022).

Furthermore, KM practices such as continuous learning and knowledge codification help organizations to build and sustain their technological competence in dynamic environments leading to more efficient technology management and innovation (Chen and Huang, 2023). The second hypothesis (H_2) has also been proved and strengthened the body of literature.

H_3. TC has positive impact on OI

The relationship between technological competence and organizational innovation has been extensively studied as the technological competence serving as a critical enabler of innovation. Research indicates that organizations with high technological competence are better equipped to develop and implement innovative solutions as they possess the necessary technical expertise, resources and capabilities to drive technological advancements (Teece, 2020). Technological competence facilitates the creation of new products, services and processes by enabling firms to leverage emerging technologies and integrate them into their operations (Guan *et al*., 2022). Moreover, organizations with strong technological capabilities can adapt more rapidly to changes in the market and technological environment that nurture a culture of continuous innovation (Li *et al*., 2023). Hence, (H_3) supports the literature explaining that it works in the Pakistani organizations as well.

H_4. *OI has positive relationship with SOP*

The last hypothesis was about the relationship between organizational innovation and sustainable organizational performance. The organizational innovation including the development of new technologies, processes and business models enables firms to adapt to changing market conditions and environmental demands which is crucial for sustainable performance (Schilke and Goerzen, 2022). The extant literature has shown that firms with strong innovation capabilities can improve their resource efficiency, reduce environmental impact and create value for both customers and society contributing to sustainable business practices (Aguirre-Urreta *et al*., 2021). Furthermore, organizational innovation fosters a culture of continuous improvement and resilience which is essential for maintaining competitive advantage and achieving sustained success over time (Teece, 2023). This last direct relationship has also been well established in this study and (H_4) has been proved.

The evidence of all direct relationships show that the variables used in this study are very much relevant and worth mentioning for consideration in future researches as well as in managerial practices. The next sections will describe the indirect relationships among the same variables as discussed above by explaining the mediating and moderating effects among the relationships one or the other. The study's ultimate objective was to find out the integrated relationship of all study variable which was the missing link in the literature which has been significantly established.

Indirect Relationships (Mediation Effects)

The second objective of this study was *"To investigate the mediating role of technological competence in the relationship between knowledge management* and *organizational innovation. Additionally, to examine the mediating effect of organizational innovation on the relationships between technological competence* and *sustainable organizational performance"* which is addressed through four hypotheses (H_6 and H_7). Both the hypotheses have been examined through statistical analyses by using sequential equation modeling and found them positive as shown in

the table 3.8 in section-3. There are significant evidences in the literature supporting the mediations of the study variables in different contexts. The findings of these indirect relationships (hypotheses H_6 and H_7) are discussed as under:

H_6. There a is significant mediation effect of TC between the relationship of KM and OI

The mediation effect of Technological Competence (TC) between the relationship of Knowledge Management (KM) and Organizational Innovation (OI) has gained significant attention in recent research. KM facilitates the creation, sharing and utilization of knowledge which consequently improves an organization's technological capabilities and enables the effective adoption and integration of new technologies (Teece, 2021). Eventually, the enhanced technological capabilities mediate the influence of KM on OI by providing the technical expertise and resources necessary for developing innovative products, processes and services (Chen *et al*., 2022). Previous studies have shown that firms with strong KM systems and technological competence are better equipped to foster innovation and maintain competitive advantage (Zhou *et al*., 2023). Thus, TC serves as a crucial mediator in leveraging KM for organizational innovation. Hence, the results of this study are favorable towards the logic of mediation role of technological competence and organizational innovation (H_6) leading to the sustainable organizational performance (SOP). In this study the mediating effect of TC on the relationship of KM and OI has also been proved.

H_7. There is a positive mediation effect of OI between TC and SOP

The previous studies also shed light on the importance of Organizational Innovation (OI) which plays a crucial mediating role between Technological Competence (TC) and Sustainable Organizational Performance (SOP). Technologically competent firms are better positioned to innovate, leveraging cutting-edge technologies to improve efficiency, reduce costs and develop sustainable products and services (Teece, 2021). OI mediates this relationship by transforming technological knowledge into novel solutions that align with environmental and social objectives which leads to drive sustainability (Zhao *et al*., 2022). Previous researches indicate that through innovation, organizations can integrate sustainable practices into their operations and improving both the financial and environmental performance (Zhou *et al*., 2023). Therefore, OI is an essential mechanism through which technological competence enhances sustainable organizational performance. Hence, the hypothesis-7 (H_7) is also in line with the literature and proved the pivotal mediating role of OI between the relationship of TC and SOP.

Sequential Mediating Relationships

The third objective of this study was "*To assess the sequential mediating effect of technological competence* and *organizational innovation on the relationship between knowledge management* and *sustainable organizational performance*" To achieve this objective, two hypotheses were formulated i.e., H_8 and the result of the analyses for this hypothesis found positive as shown in the table 3.9, section-3. The discussion on both the relationships in comparison with the previous studies exist in the extant literature is as under:

H_8. There is a sequential mediation of TC and OI between KM and SOP

While the literature extensively discusses the individual relationships between Knowledge Management (KM), Technological Competence (TC), Organizational

Innovation (OI) and Sustainable Organizational Performance (SOP), however, the sequential mediation of Technological Competence (TC) and Organizational Innovation (OI) in the relationship between KM and SOP remains underexplored. Existing studies suggest that KM enhances both technological capabilities (Teece, 2021) and innovation (Zhou *et al*., 2023) which contribute to improve organizational performance. However, there is limited research examining how these factors operate sequentially as mediators, with TC influencing OI, which then drives SOP. This gap highlights the need for further investigation into how KM indirectly impacts sustainable performance through these integrated pathways. Exploring this sequential mediation could provide valuable insights into the complex mechanisms by which organizations leverage knowledge to achieve long-term sustainability, offering both theoretical and practical contributions to the field. Therefore, examining this integrated link, this study presents a unique opportunity for advancing the understanding of KM's role in sustainable organizational success.

The results evidently indicate that the organizations are required to integrate the highly discussed competences like technological, marketing and organizational innovation in their knowledge management systems enabling organizations to achieve sustainable competitive advantage for the long time.

Moderation Analysis

The fourth objective of the study was "*To examine the moderating effect of big data analytics on the relationship between knowledge management* and *technological competence.*" For this purpose, based on the insights obtained from the literature, big data analytics was selected as moderator which is highly important for managers and practitioners in their decision making process based on the updated and relevant information/data. To examine the moderating effect on the relationships between KM and TC, a hypothesis (H_5) was formulated and tested statistically by using AMOS statistical tool.

H_5. BDA moderates the relationship between KM and TC

To examine the role of big data analytics on the relationship of KM and TC, the moderating hypothesis was formulated and tested and the results are quite positive indicating the importance of emerging technology in organizational systems. Though the individual effects of Knowledge Management and Technological Competence have been well studied in the literature but little is known about the moderating function of Big Data Analytics in the interaction between KM and TC. In order to improve technological skills, knowledge management (KM) makes it easier for an organization to create, share and apply knowledge (Teece, 2021). However, by allowing enterprises to leverage massive volumes of data, recognize technology trends and maximize technological decision-making, BDA can greatly deepen this link (Chen *et al*., 2022). BDA gives businesses the means to glean insightful information from complicated data, which enhances the efficacy and efficiency of innovation and technology adoption processes (Zhang *et al*., 2023). As discussed earlier, BDA serves as a critical moderating factor that enhances the positive influence of KM on TC, allowing firms to better align their technological capabilities with the rapidly evolving digital landscape. This highlights the importance of incorporating big data strategies to fully leverage KM for technological advancement.

In nut shell, the analyses of both the relationships suggest that Big Data Analytics (BDA) does not just affect the direct relationship between KM and the outcomes (TC, MC)

but actively strengthens these relationships as making it a key factor in optimizing the impact of KM practices in IT intensive organizations of the province of the Punjab, Pakistan. Hence, it is established that the integrated relationships between knowledge management and organizational competences i.e, marketing competence, technological competence and organizational innovation by incorporating the big data analytics technology into the system is crucial for sustainable organizational performance.

RESEARCH IMPLICATIONS

This study provides significant theoretical contributions to the literature on Knowledge Management (KM), Dynamic Capabilities Theory (DCT), and the Knowledge-Based View (KBV). It enriches these theoretical domains by integrating emerging technologies such as Big Data Analytics (BDA) with established strategic frameworks to explore their collective impact on Sustainable Organizational Performance (SOP). Prior studies have frequently explored KM, technological competence, and innovation in isolation. However, this study advances the literature by offering an integrated model that demonstrates the interplay of these constructs, particularly in the context of a developing country like Pakistan. This contributes a much-needed perspective to global organizational research, where non-Western contexts have often been underrepresented. A key theoretical advancement lies in the inclusion of BDA as a moderating factor in the KM–technological competence (TC) relationship. This addition expands the traditional KM framework and aligns with the findings of Chen et al. (2024) and Ahmed (2024), who suggest that technological tools enhance the effectiveness of knowledge systems. The study empirically validates that BDA strengthens the influence of KM on TC, offering a robust theoretical foundation to support its role as a strategic enabler. This aligns with earlier research by Anshari and Hamdan (2022), and Abu Zaid and Ahmed Al-Shura (2022), reinforcing BDA's utility as a crucial enhancer of organizational capabilities.

Moreover, this study extends the Dynamic Capabilities Theory by empirically confirming the sequential mediation effect of TC and Organizational Innovation (OI) in the KM–SOP linkage. This responds to critiques, such as those by Brock and Hitt (2024), that DCT has been rich in theoretical insight but lacking empirical validation. By illustrating how innovation functions as a dynamic capability, the study supports the argument made by Hislop, Bosua, and Helms (2018) that innovation drives organizational sustainability in dynamic environments. Similarly, the study reinforces the Knowledge-Based View by showing how KM, when supported by technological competencies, leads to a sustainable competitive advantage. The findings of Nguyen, Sharma, and Malik (2024) support this conclusion, and the integration of BDA into this framework broadens the scope of KBV by introducing advanced technological dimensions, especially within developing economies. In addition to its theoretical contributions, the study offers practical insights for organizational leaders. Managers are encouraged to adopt a strategic and holistic approach to managing knowledge and technology by integrating KM practices with BDA and innovation strategies. The findings emphasize that organizations seeking sustainable performance should not only foster a culture of knowledge sharing but also embed technological capabilities into these practices.

This integrated approach can enhance decision-making processes, increase innovation capacity, and improve overall performance. For practitioners in non-Western settings, particularly within local industries in Pakistan, the study presents applicable recommendations. While global trends focus on cutting-edge

infrastructures, local firms can derive significant benefits from cost-effective solutions, such as leveraging existing data repositories or using cloud-based analytics tools. The moderating role of BDA offers local managers valuable insights into optimizing decision-making, thereby enhancing competitiveness and sustainability in both local and global markets.

Nonetheless, the study is not without limitations. First, its reliance on cross-sectional data restricts the ability to infer causality. Longitudinal research would be beneficial to observe how KM, TC, OI, and SOP interact over time. Second, the sample is limited to IT-intensive firms in Punjab, which may constrain the generalizability of the findings. Including a broader range of industries and geographic regions would enhance external validity. Third, the study did not explore other potential influencing factors, such as leadership style, organizational culture, or environmental uncertainty, which may affect the observed relationships.

Future research could build upon this study by incorporating contextual variables such as industry type, organizational size, or location to better understand the dynamics of KM in diverse environments. A longitudinal research design could provide valuable insights into the evolving impact of KM on innovation and sustainability over time. Furthermore, integrating emerging technologies such as Artificial Intelligence (AI) and blockchain into the KM framework could be a fruitful area of exploration. Investigating how these technologies interact with KM and BDA would significantly expand the digital transformation literature. In particular, exploring the synergies between AI, blockchain, and KM could yield practical strategies for improving decision-making, enhancing organizational capabilities, and ensuring long-term sustainability.

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