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ORIGINAL ARTICLE

Fueling big data analytics for project success: Mediating role of knowledge sharing and innovation performance

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ABSTRACT

Purpose: Drawing on the Resource Based View (RBV) and Dynamic Capabilities Theory (DCT), the study seeks to investigate the impact of Big Data Analytics (BDA) on Project Success (PS) through Knowledge Sharing (KS) and Innovation Performance (IPF). **Design/ Methodology:** Survey data were collected from 422 senior-level employees in IT companies, and the proposed relationships were assessed using the SMART-PLS 4 Structural Equation Modeling tool. **Findings:** The results show a positive and significant indirect effect of big data analytics on project success through knowledge sharing. IPF significantly mediated the relationship between BDA and PS in IT companies. **Originality/Value:** This study is one of the first to consider big data analytics as an essential antecedent of project success. With little or no research on the interrelationship of big data analytics, knowledge sharing, innovation performance, and organizational performance, the study investigates the mediating role of knowledge sharing and innovation performance on the relationship between BDA and PS. **Implications:** This study, grounded in RBV and DCT, investigates BDA's influence on PS through KS and IPF. Implications encompass BDA's strategic role, KS and IPF mediation, and practical and research-based insights. Findings guide BDA integration, collaborative cultures, and sustained success.

KEYWORDS

project success; big data analytics; knowledge sharing; innovation performance

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1. Introduction

The rapid emergence of innovative technology in the global economic environment has brought about a fundamental revolution across all industries (Beer, 2023). As a result of this shift, the IT sector needs to adapt its operations accordingly. Big data is a significant game-changer in how businesses operate across various industries. Big data encompasses organized and unstructured data, such as photographs and videos, which have been used increasingly (Favaretto et al., 2020). Big data analytics (BDA) has emerged as a novel approach to extracting patterns from raw data, transforming the competitive landscape of the corporate world. It enables informed decision-making, drives innovation upgrades, enhances productivity, and generates knowledge (Lutfi et al., 2023). The components of BDA can be broadly categorized into six aspects: data generation, acquisition, storage, advanced data analytics, visualization, and value-creation decision-making (Saggi and Jain, 2018).

Business analytic data encompasses the strategies, technologies, systems, processes, procedures, and applications that evaluate crucial business data, enabling enterprises to understand their business and market better and make timely and informed decisions (Wu et al., 2023). BDA plays a vital role in comprehending large volumes of data, extracting valuable information and knowledge, and through interpretation and categorization, facilitating more efficient management (Patrucco et al., 2023). BDA has gained significant attention among academics and management as an organization's ability to handle, process, and analyze big data (Elia et al., 2022). Effective knowledge management is essential for managers to leverage their backgrounds and talents within and outside traditional organizational boundaries in all innovation endeavors (Dwivedi et al., 2023). Consequently, organizations with extensive knowledge management experience demonstrate higher innovativeness (Hayaeian et al., 2022) and better use of internal resources like BDA. The firm's ability to manage and integrate new and existing knowledge can enhance the positive impact of BDA on performance (Saeed et al., 2023). In the context of project-based companies, BDA proves valuable in decision-making processes. By analyzing vast and complex data sets, project-based businesses can effectively plan and allocate resources (Maheshwari and Kamble, 2023).

However, understanding the relationship between BDA and PS remains limited. A search of peer-reviewed databases yielded minimal research that directly links BDA with PS (Ahmed et al., 2022). Moreover, existing studies suggest that the relationship between BDA and project success may be more intricate than a simple direct association. The literature provides some support for the argument that BDA can enhance Knowledge Sharing (KS) within an organization (Barlette and Baillette, 2022) and drive Innovation Performance (IPF) (Rahimi et al., 2022), ultimately contributing to improved project success. However, empirical evidence supporting these claims is scarce. Studying the mediating impact of KS between big BDA and PS is crucial. It reveals how BDA insights are transmitted within organizations, fostering collaboration and informed decision-making (Saggi and Jain, 2018). This exploration also uncovers the translation of data insights into practical strategies and contributes to a holistic understanding of BDA's influence on project outcomes (Barlette and Baillette, 2022). Recognizing knowledge sharing's role informs effective BDA implementation by highlighting the importance of a conducive environment for insights exchange. Also, studying the mediating role of IPF in the relationship between BDA and PS is vital. It reveals how data analytics drives innovation, expanding project success beyond direct outcomes (Behl et al., 2023). This exploration will offer insights into leveraging BDA for both immediate project optimization and long-term organizational growth.

Consequently, there are notable research gaps concerning the interrelationships between BDA, KS, IPF, and Project Success (PS), particularly when considering the challenges posed by knowledge sharing in the modern era's complex and chaotic societal developments.

Firstly, despite the growing interest in BDA, the concept remains relatively underdeveloped (Mikalef et al., 2019). The literature on big data analytics has made its way into the realm of project success (Williams, 2017). Secondly, research has demonstrated a significant correlation between data analytics and project outcomes, specifically in project governance (Young et al., 2020) and project management (Cooke-Davies, 2002). Thirdly, the relationship between BDA and PS has been explored in the context of various mediating variables. BD adoption has proven beneficial for specific organizations, particularly in performance improvement. Many studies have established a link between BD success and positive business outcomes, with larger organizations implementing BD for purposes such as predicting market trends, analyzing customer behavior, enhancing customer experiences, and identifying opportunities for improvement (Lutfi et al., 2023). While existing research has examined the impact of big data analytics on project success through moderating variables (Ahmed et al., 2022), there is a need to explore further how other variables can mediate the relationship between BDA and PS, providing a deeper understanding of how big data analytics can contribute to improved project success. As no research has investigated the influence of BDA on KS and innovation performances as mediators, it can be hypothesized that big data analytics significantly impacts knowledge sharing and innovation performances. Fourthly, Mangla et al. (2021) examined the association between BDA and PS in the construction industry. Their findings suggested that project management tools and practices mediate the relationship between BDA and PS. However, the study's narrow focus on a single sector remains uncertain whether these findings can be generalized to other businesses. Future studies should examine the effect of BDA on PS across various sectors to address this gap. Lastly, KS and innovation have been identified as potential mediators in the relationship between big data analytics and innovation (Obitade, 2021; Su et al., 2022). However, no research has assessed the mediating effect of KS and IPF in the relationship between BDA and PS.

The present study employs the resource-based view theory (RBV) and the dynamic capability theory (DCT) to elucidate the interrelationships among big data analytics, knowledge sharing, innovation performance, and project success. According to RBV, sustainable competitive advantage stems from a company's ability to acquire and control valuable, rare, unique, and irreplaceable resources and capabilities and effectively utilize them within the organization (J. Barney et al., 2001). RBV evaluates and interprets organizational resources to comprehend sustainable competitive advantage, emphasizing hard-to-imitate business attributes as sources of superior performance and competitive edge (J. B. Barney, 1986). Resources that require extensive learning or significant cultural changes tend to be more unique to the business, making them more challenging for competitors to replicate. Dynamic capability theory focuses on the firm's resource processes, including integration, reconfiguration, gain, and release, which enable the firm to adapt and even shape changes in the market. As markets emerge, converge, diverge, evolve, and decline, organizations' strategic and organizational routines create new resource configurations (Eisenhardt and Martin, 2000). This theory describes an organization's capacity to integrate, develop, and reconfigure internal and external capabilities in response to rapidly changing conditions (Teece, 2007). The dynamic capability enables a company to utilize its resources effectively to adapt to the evolving business environment, ultimately creating a competitive advantage (Baden-Fuller and Teece, 2020).

This research aims to address the identified knowledge gaps and significantly contribute to the field. Firstly, it extends the existing research on the impact of BDA on PS (Kastouni and Lahcen, 2020; Mangla et al., 2021). This study is among the pioneering works that consider big data analytics as a crucial antecedent of PS, specifically in IT companies. Secondly, given the limited research on the effects of BDA on KS and IPF, this study explores whether big data analytics is a significant predictor of these factors. Thirdly, the study further investigates whether KS and IPF act as mediating variables in the relationship between BDA and PS. This analysis will shed light on the mediating mechanism through which big data analytics influences project success, contributing to a more comprehensive theoretical understanding. Fourthly, this research enriches the literature on KS and IPF and contributes to understanding the role of BDA in fostering project success. Moreover, the study provides valuable insights into the resource-based view (RBV) and dynamic capability theory (DCT) by illustrating how big data analytics contributes to project success through knowledge sharing and innovation performance. The research contributes to data analytics by examining the implications of BDA for PS in small and medium-sized companies.

In an era characterized by data-driven decision-making, the role of BDA in shaping organizational success has gained prominence. This study, framed within the RBV and DCT, takes a pioneering step in investigating how BDA impacts PS by exploring the pathways of KS and IPF. As industries become increasingly reliant on data insights for competitive advantage, understanding the intricate relationship between BDA and PS becomes imperative. However, despite the growing significance of BDA, limited research delves into its interplay with knowledge sharing, innovation performance, and organizational success. This study addresses this research gap, emphasizing the mediating roles of KS and IPF, and thus, offers a comprehensive understanding of how BDA contributes to sustained project and organizational success. To ascertain the impact of BDA on PS through KS and IPF, the study utilizes a survey that is distributed in the IT sector of Peru (detailed methodology is presented in Section 3).

2. Theoretical background and hypotheses development

2.1. Big data analytics

The term "big data" has been in use since the 1990s, with some attributing its popularity to US computer scientist and entrepreneur John Mashey. However, its initial usage in computer science referred to methods of displaying data (Sarker, 2022). In the early 2000s, Gartner analyst Doug Laney further popularized and defined "BD" in the management and business context (Mariani et al., 2018). Since its inception (Jahani et al., 2023), academics have extensively studied big data across various fields, including information management, supply chain management, marketing, and financial management. However, the mere presence of large volumes of diverse data does not guarantee to generate relevant knowledge. To be effective, data analytics must encompass a comprehensive process of accessing, storing, analyzing, and interpreting data to extract meaningful insights (Mariani and Baggio, 2022).

According to Chong and Shi (2015), BDA can be classified into the following categories: a) big data acquisition and storage, b) big data programming model, c) big data analysis, and d) benchmarking. Big data acquisition involves collecting data in a well-structured digital format for subsequent storage and analysis (Cuzzocrea et al., 2011). Big data storage focuses on the effective management and storage of large-scale datasets with a focus on dependability and accessibility (Chen et al., 2014). The big data programming model is designed to facilitate the mapping of parallel environments to applications, encompassing concepts such as map reduction, graph processing models, and stream processing models (Cohen, 2009; Dean and Ghemawat, 2008; Sakr, 2013). Data analysis aims to extract information from numerous sources for various applications, including decision-making and prediction. However, compared to traditional data analysis, big data's large, heterogeneous, and diverse sources pose significant challenges to knowledge discovery and data mining (Chong and Shi, 2015).

2.2. Big data analytics and project success

Jugdev et al. (2013) propose a two-stage division of project success, with the first stage involving critical factors contributing to the achievement of PS, and the second stage encompassing project success standards used to evaluate whether a project was successful. In the era of data-driven decision-making, organizations increasingly focus on enhancing their business models through process automation and adopting innovative approaches to maximize their commercial value (O'Driscoll, 2014). The literature suggests that analyzing big data can enable organizational leaders to leverage data insights more effectively and make informed decisions (Ahmed et al., 2022). This, in turn, helps generate, deliver, and secure higher business value in both short- and long-term project horizons, leading to the development of the research model.

The relationship between BDA and PS can be understood through the lens of the RBV theory. BDA is considered a valuable resource that market mechanisms cannot easily replicate. Its utilization can enhance project success and provide a sustainable competitive advantage (Lu and Ram, 2011). Furthermore, applying BDA has been shown to improve firm performance regarding environmental and social sustainability, thereby positively influencing project success (Mangla et al., 2021). Organizations leveraging BDA technology differentiate themselves from competitors and increase project success rates (Kastouni and Lahcen, 2020). BDA significantly impacts project success by providing data-driven insights for informed decision-making, efficient planning, proactive risk management, optimized resource allocation, stakeholder engagement, innovation, and continuous improvement (Karaboga et al., 2022). BDA's ability to analyze historical and real-time project data enhances project management strategies, leading to better outcomes and fostering a culture of learning and adaptation for long-term success (Garmaki et al., 2023).

H1: BDA has a significant and positive impact on PS.

2.3. The mediating role of knowledge sharing

Nonaka (1994) and Alavi and Leidner (2001) have described knowledge as a collection of justified beliefs that can be organized and managed to enhance organizational performance through practical action. There are three key knowledge processes: a) knowledge acquisition, which involves developing new knowledge from data and information; b) knowledge conversion, which entails making acquired knowledge valuable to the organization by structuring it or transforming tacit knowledge into explicit knowledge; and c) knowledge application, which involves utilizing knowledge to accomplish tasks (Alavi et al., 2006; Gasik, 2011; Gold et al., 2001).

The relationship between BDA and KS can be elucidated through the RBV theory. Many businesses have utilized resources like BDA to facilitate KS and gain a competitive advantage across various sectors (Constantiou and Kallinikos, 2015). Within IT organizations, employees extensively employ big data analytics and knowledge-sharing practices to achieve project budgetary goals and increase project success (Serrador and Pinto, 2015). Furthermore, firms that have successfully integrated big data analytics into various company functions and fostered knowledge sharing have witnessed the expected return on investment for their projects (Grover et al., 2018).

In knowledge management, KS is defined as identifying existing and available knowledge, transferring it, and applying it to perform tasks more efficiently, rapidly, and cost-effectively than possible (Christensen, 2007). Thus, sharing knowledge, ideas, and information within a team can lead to quicker problem-solving than seeking external assistance, which may incur additional expenses and pose challenges to project success (Pearce, 2004). In agile IT projects, where teams are relatively small, and every member actively participates in decision-making and shares knowledge with teammates, joint project success is achieved (feeling like a leader).

The relationship between KS and PS can be understood through the lens of DCT. Business capabilities, such as knowledge sharing, enable companies to communicate information related to changes in focal product technologies, ultimately enhancing organizational performance and increasing the likelihood of PS (Behl et al., 2023). Employees who engage in knowledge exchange with their colleagues have more opportunities for innovation and increased productivity, thereby contributing to successful project completion within scheduled goals (Kharub et al., 2023). KS could serve as a vital mediator between BDA and PS. By facilitating the effective dissemination of BDA-derived insights, it empowers teams to make informed decisions, adapt strategies, and identify opportunities in real-time. This active information flow enhances collaboration, aligns goals, and leverages data-driven intelligence, thereby positively impacting project outcomes (Hasan et al., 2022).

H2: There is a significant and positive impact of BDA on KS.

H3: There is a significant and positive impact of KS on PS.

The literature indicates that BDA can influence KS (Constantiou and Kallinikos, 2015) and contribute to PS (Kharub et al., 2023). Based on this premise, the following hypothesis is proposed:

H4: KS mediates the relationship between BDA and PS.

2.4. The mediating role of innovation performance

Over time, innovation has become closely associated with economic ideology, as nations recognize it as a source of international competitiveness and a solution to financial challenges (Drejer, 2004). Industrial leadership benefits from innovation by enhancing productivity (Robertson et al., 2021). Businesses with solid competencies in business analytics, knowledge management, and agility are better positioned to achieve innovation. Theories of knowledge management suggest that companies utilizing big data analytics possess a distinct advantage in fostering innovation (Khan and Tao, 2022). BDA can potentially drive innovation across various consumer domains, including innovation performance (Y. Wang and Hajli, 2017). BDA has transformed the competencies necessary for organizations to innovate and succeed (Lehrer et al., 2018). Yang et al. (2015) argue that companies capable of utilizing big data analytics are more likely to innovate and achieve success. By employing big data analytics, companies can enhance operational efficiency and achieve more significant revenue growth than their competitors (Marshall et al., 2015). Therefore, big data represents a valuable asset for driving company innovation performance (Khan and Tao, 2022).

The relationship between big data analytics and innovation performance can be explained within the resource-based view framework. Business resources, such as BDA, have been leveraged to differentiate companies. By utilizing the information technology ecosystem, companies can transform data into a decision-making resource that positively impacts innovation (Rivera and Shanks, 2015). BDA serves as a competitive differentiator (Jeble et al., 2018) that positively influences organizations' innovation performance (Ramakrishnan et al., 2012). Previous studies demonstrate that big data analytics drives innovation across the entire company system, from product to process, infrastructure to segmentation (Khan and Tao, 2022).

Innovation projects are increasingly becoming the cornerstone of RandD activities within organizations as they enhance organizational performance and ensure project success (Shenhar and Dvir, 2013). Cultivating an innovative environment and establishing high-quality networks enhance the position of organizations and increase the likelihood of project success (Ruoslahti, 2020). Companies that prioritize innovation to improve the quality of their products have witnessed the anticipated return on investment (H. Wang et al., 2022). Furthermore, organizations that develop new technologies to enhance their operational processes experience increased project profitability (Wamba-Taguimdje et al., 2020).

The relationship between IPF and PS can be understood through the lens of DCT. Business capabilities, such as innovation performance, require integrating knowledge across diverse abilities within the innovation ecosystem. Collaborators exchange and combine various knowledge combinations to foster creativity (Moller and Rajala, 2007). In a constantly changing world of markets, products, and technology, the dynamic nature of knowledge as a valuable and irreplaceable resource (J. Barney, 1991) assumes greater significance as a driver of innovative performance. BDA generates insights that can drive innovative solutions, and when effectively translated into practical innovations, these contribute to project success (Shirazi et al., 2022). IPF acts as the conduit, as it guides the transformation of data-driven insights into creative solutions, process improvements, and novel approaches. This bridge between BDA and PS underscores the pivotal role of innovation in maximizing the impact of data analytics on project outcomes (Edu, 2022).

H5: There is a significant and positive impact of BDA on IPF.

H6: There is a significant and positive impact of IPF on PS.

The literature above suggests that BDA can impact IPF (Jeble et al., 2018), which can in turn project success (Wamba-Taguimdje et al., 2020). Hence, the following hypothesis is proposed:

H7: IPF mediates the relationship between BDA and PS.

The proposed model is as follows (**Figure 1**).

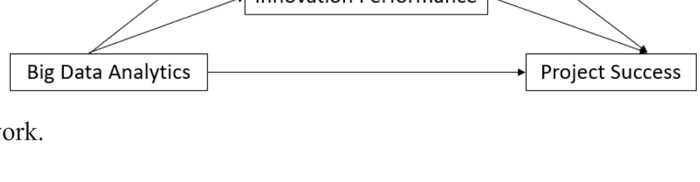

Figure 1. Research framework.

3. Methodology

3.1. Research firms

The study sample for this research comprises IT companies due to their extensive range of big data analytics capabilities (Muller et al., 2016). Moreover, high-tech firms require a distinct approach to managing knowledge sharing compared to non-knowledge organizations, with innovation playing a strategic role (Donate and de Pablo, 2015).

3.2. Sample and data collection

This study utilized non-probability convenience sampling to select participants. Data collection was conducted through an electronic questionnaire. An impartial academic group reviewed the questionnaire's content to ensure its validity. The target respondents for this survey were small and medium-sized IT enterprise owners in Peru. Before participating, participants were informed about protecting their anonymity and confidentiality. They received a brief survey invitation explaining the study's purpose, potential risks, and questions. Data collection took place between November and December of 2022. A total of 500 questionnaires were distributed, out of which 450 were returned, resulting in a response rate of 90%. After eliminating incomplete responses, 422 valid responses were used for analysis. The sample encompassed various provinces in Peru, including Arequipa, Trujillo, Piura, Callao, and Lima. The demographic information of the respondents is presented in **Table 1**.

Table 1. Demographic information.

	Category	Atribute	Count	Percentage (%)
Individual demographics	Gender	Male	385	91.230%
		Female	37	8.770%
	Age	<25	105	24.880%
		25–29	98	23.220%
		30–34	48	11.370%
		35–39	58	13.740%
		>40	113	26.780%
	Education	High school	75	17.770%
		Bachelors	260	61.610%
		Master or MBA	79	18.720%
		Ph.D or DBA	8	1.900%
	Provinces	Lima	150	35.550%
		Callao	80	18.960%
		Arequipa	98	23.220%
		Trujillo	50	11.850%
		Piura	44	10.430%

3.3. Measures

To ensure the study's validity and minimize cultural bias, the researcher employed a standardized methodology suitable for the survey (Boer et al., 2018). The survey items were initially developed in English with the assistance of two professors. Each questionnaire item underwent direct translation and back-translation to ensure the quality of the translation. Five IT CEOs were also invited to participate in a pilot test to address language and comprehension challenges. The questionnaire was revised based on their feedback to ensure accuracy and validity. All items were rated on a 5-point Likert scale, ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

The measurement of BDA utilized a scale developed by Lin et al. (2022). The scale consists of four items that assess how an organization operates big data analytics (e.g., “Our organization has successfully integrated big data into various business processes”). PS was measured using a scale developed by Aga et al. (2016), comprising eight items that evaluate the success of the project (e.g., “The project was completed within the allocated time and budget”). KS was measured with a scale developed by Azeem et al. (2021), which consists of four items capturing how an organization shares knowledge (e.g., “Our employees rely on their experience, skills, and knowledge in their work”). IPF was measured using a scale developed by Chang et al. (2012), which includes five items assessing the organization’s level of innovation (e.g., “The company generates significant profit from its new products/services”).

3.4. Data analysis methods

Data analysis was conducted using Smart-PLS 4. The application of Partial Least Squares Structural Equation Modeling (PLS-SEM) involves two main steps: measurement model assessment and structural model evaluation (Ringle et al., 2018). The measurement model selects constructs based on high indicator loadings, convergence, compound reliability (CR), and discriminant validity. The structural model’s bootstrap evaluation examines the path coefficients’ size and significance. For the most detailed mediation analysis, the method proposed by Preacher and Hayes (2008) is commonly used and well-suited for PLS-SEM (Hair Jr et al., 2014).

4. Results

4.1. Measurement model assessment

The first step in PLS-SEM analysis is evaluating the measurement model, which ensures the reliability of constructs, convergent validity, and discriminant validity. Initially, the factor loadings were examined. While factor loadings exceeding 0.70 are preferred, it is common for researchers in the social sciences to obtain outer loadings below this threshold. Instead of immediately removing indicators, it is essential to assess the impact of item removal on composite reliability, content, and convergent validity. Items with outer loadings between 0.40 and 0.70 should only be removed if their deletion improves the composite reliability or brings the extracted average variance (AVE) within the recommended range (Hair et al., 2019). The factor loading of the measurement model is shown in **Figure 2**.

In addition to examining the outer loadings, Cronbach’s alpha and composite reliability were employed to assess the reliability of the constructs. The study’s findings revealed that all constructs exhibited acceptable reliability levels above 0.700. Convergent validity, which measures the reliability of the concepts, was evaluated using the Average Variance Extracted (AVE). Since the AVE exceeded 0.500, the results demonstrate good convergent validity. **Table 2** presents the

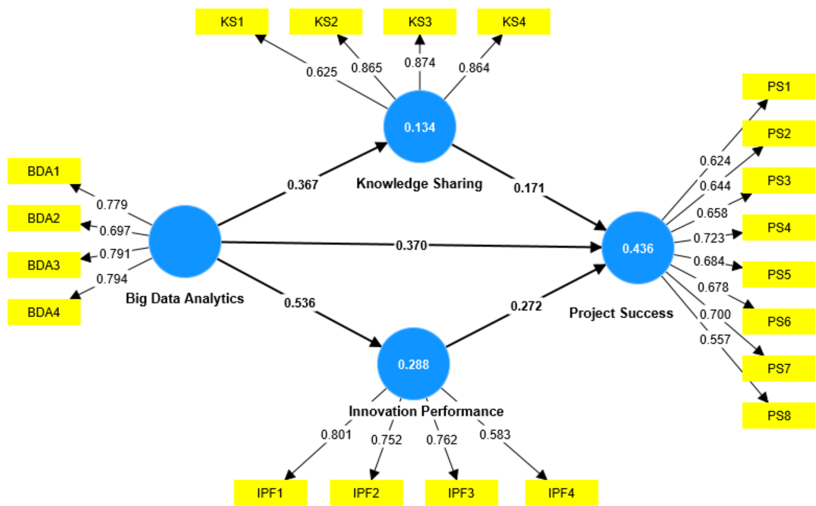

Figure 2. Measurement model analysis.

Table 2. Construct reliability and validity.

Construct	Item	Outer loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Big Data Analytics (BDA)	BDA1: Our organization often uses big data analytics technology.	0.779	0.764	0.850	0.587
	BDA2: Employees of our organization are frequent users of big data analytics technology.	0.697			
	BDA3: Our organization has realized the integration of big data in various business processes.	0.791			
	BDA4: Big data-related analysis and prediction capabilities are often used during our business processes.	0.794			
Innovation Performance (IPF)	IPF1: The company has improved its product/service quality through innovation.	0.801	0.700	0.818	0.532
	IPF2: The company has accelerated the commercialization pace of new products/services through innovation.	0.752			
	IPF3: The company makes a considerable profit from its new products/services.	0.762			
	IPF4: The company develops new technology to improve the operation process.	0.583			
Knowledge Sharing (KS)	KS1: Our employees exchange knowledge with their co-workers.	0.625	0.824	0.885	0.663
	KS2: In their work, our employees rely on experience, skills, and knowledge.	0.865			
	KS3: In the relationship, we frequently adjust our shared understanding of end-user needs, preferences, and behaviors.	0.874			
	KS4: Our companies exchange information related to changes in the technology of the focal products.	0.864			

Table 2. (*Continued*).

Construct	Item	Outer loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Project Success (PS)	PS1: The project was successful.	0.624	0.818	0.860	0.436
	PS2: The project has satisfactorily met the budget goals.	0.644			
	PS3: The project has satisfactorily met the schedule goals.	0.658			
	PS4: The project has satisfactorily delivered the required outputs (i.e., fulfilled its requisites).	0.723			
	PS5: Project's outputs have supported the business to produce the expected outcomes.	0.684			
	PS6: Undesired outcomes were managed and avoided.	0.678			
	PS7: The project has provided the expected return on investment.	0.700			
	PS8: The project's outcomes adhered to the outcomes planned in the business case.	0.557			

reliability and validity of the model.

Discriminant validity was established by comparing the correlations among the latent variables to the square root of AVE and the heterotrait-monotrait correlation ratio (Henseler et al., 2015), with values below the (conservative) threshold of 0.850. Thus, discriminant validity is confirmed. The outcomes of the discriminant validity analysis are presented in **Tables 3** and **4**.

Table 3. Fornell-Larcker criterion.

	BDA	IPF	KS	PS
BDA	0.766	–	–	–
IPF	0.536	0.730	–	–
KS	0.367	0.447	0.814	–
PS	0.578	0.546	0.428	0.660

Table 4. Heterotrait-monotrait ratio (HTMT).

	BDA	IPF	KS	PS
BDA	–	–	–	–
IPF	0.722	–	–	–
KS	0.446	0.581	–	–
PS	0.694	0.679	0.524	–

4.2. Structural model

The next step involves assessing the structural model to validate the proposed relationships. The structural model represents the hypothesized paths in the research framework.

Examining the R2 values, the results indicate that big data analytics can explain 13.4% of the variation in knowledge sharing. Additionally, big data analytics can account for 28.8% of the variation in innovation performance. Furthermore, 43.6% of the variation in project success can be attributed to the combined effects of knowledge sharing and innovation performance. Moreover, the Q2 values establish the predictive relevance of the endogenous constructs. A Q2 value above 0 indicates that the model has predictive relevance. The results demonstrate significant predictive power for the constructs (see **Table 5**).

Table 5. Hypotheses results and predictive relevance.

	β	SD	*t* statistics	*p* values
(H1) BDA > PS	0.370	0.055	6.756	0.000
(H2) BDA > KS	0.367	0.051	7.166	0.000
(H3) KS > PS	0.171	0.046	3.681	0.000
(H5) BDA > IPF	0.536	0.039	13.650	0.000
(H6) IPF > PS	0.272	0.050	5.477	0.000
	Q^2 predict			
IPF	0.279			
KS	0.127			
PS	0.323			

H1 evaluates the impact of big data analytics on project success. The results indicate a significant positive impact of big data analytics on project success (β = 0.370, t = 6.893, p = 0.000), thus supporting H1. H2 examines the impact of big data analytics on knowledge sharing. The findings reveal a significant positive impact of big data analytics on knowledge sharing (β = 0.367, t = 7.166, p = 0.000), supporting H2. H3 investigates the impact of knowledge sharing on project success. The results show a significant positive impact of knowledge sharing on project success (β = 0.171, t = 3.681, p = 0.000), supporting H3. H5 assesses the impact of big data analytics on innovation performance. The findings indicate a significant positive impact of big data analytics on innovation performance (β = 0.536, t = 13.650, p = 0.000), supporting H5. Lastly, H6 explores the impact of innovation performance on project success. The results reveal a significant positive impact of innovation performance on project success (β = 0.275, t = 5.477, p = 0.000), supporting H6. The structural model is presented in **Figure 3**.

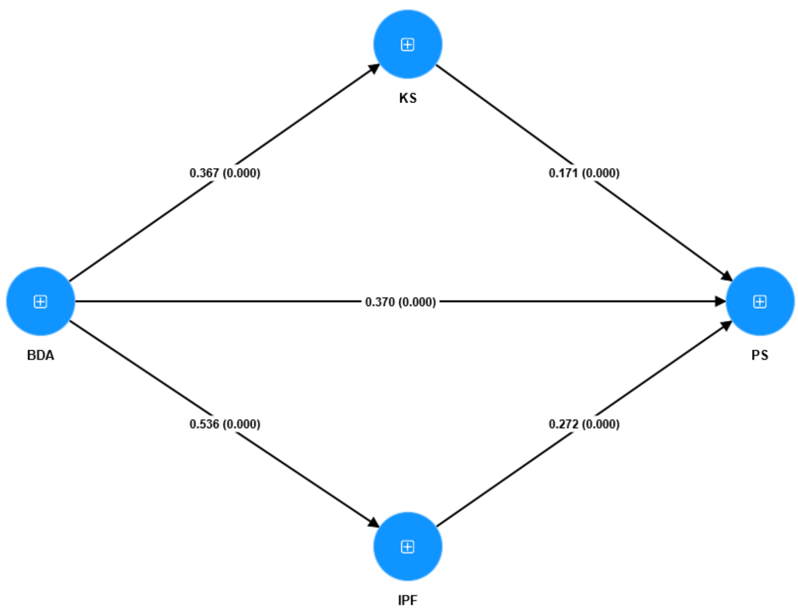

Figure 3. Structural model.

4.3. Mediation analysis

Mediation analysis examined the mediating effects of knowledge sharing and innovation performance in the relationship between BDA and PS. The results indicate that knowledge sharing significantly mediates the relationship between BDA and PS (β = 0.063, t = 3.296, p = 0.000), supporting H4. Furthermore, the findings reveal a significant indirect effect of big data analytics on project success through innovation performance (β = 0.146, t = 5.336, p = 0.000), supporting H7. The results of the mediation analysis are presented in **Table 6**.

Table 6. Mediation analysis.

Total effect	β	*t* statistics	*p* values	Direct effect	β	*t* statistics	*p* values	Hypotheses	β	SD	*t* statistics	*p* values
BDA > PS	0.578	14.787	0.000	BDA > PS	0.370	6.756	0.000	(H4) BDA > KS > PS	0.063	0.019	3.296	0.000
								(H7) BDA > IPF > PS	0.146	0.027	5.336	0.000

5. Discussion

5.1. Discussion

This study aims to examine the impact of BDA on PS through KS and IPF. The results indicate a significant direct effect of BDA on PS (H1), which aligns with previous research highlighting the considerable impact of big data analytics on project success (Jugdev et al., 2013; O'Driscoll, 2014). These findings support the RBV theory, suggesting that BDA is a valuable resource that enhances project success and provides a sustainable competitive advantage (Lu and Ram, 2011). Furthermore, utilizing BDA improves a company's environmental and social sustainability and positively impacts PS (Mangla et al., 2021). Organizations that leverage big data analytics differentiate themselves from competitors and increase the proportion of successful projects (Kastouni and Lahcen, 2020).

Additionally, the study reveals that BDA has a significant impact on KS (H2), which is consistent with previous research highlighting the influence of BDA on KS (Alavi et al., 2006; Gasik, 2011; Gold et al., 2001). These findings align with the RBV theory, indicating that many businesses employ BDA to facilitate KS and gain a competitive advantage (Constantiou and Kallinikos, 2015). Integrating BDA and knowledge exchange within IT organizations contributes to achieving budgetary goals and overall success (Serrador and Pinto, 2015). Moreover, the successful integration of BDA across various organizational activities and effective information sharing leads to the expected return on investment (Grover et al., 2018).

The study reveals that KS significantly impacts PS (H3), which aligns with previous research demonstrating the influential role of knowledge sharing in project success (Christensen, 2007; Pearce, 2004). These findings support the DCT, suggesting that business capabilities, such as knowledge exchange, enable organizations to effectively communicate information related to technological changes in their products, thereby increasing the likelihood of project success (Behl et al., 2023). Employees who actively share their expertise with colleagues have more significant opportunities for innovation and increased productivity, thus contributing to achieving project objectives within the set timeline (Kharub et al., 2023).

Furthermore, the study indicates that BDA has a significant impact on IPF (H5), which is consistent with previous research highlighting the significant influence of BDA on IPF (Lehrer et al., 2018; Y. Wang and Hajli, 2017). These findings align with the RBV, emphasizing that business resources such as big data analytics can differentiate companies by leveraging the information technology ecosystem to transform data into a valuable resource for decision-making, thereby positively affecting innovation (Rivera and Shanks, 2015). The study conducted by Jeble et al. (2018) concluded that big data analytics serves as a competitive differentiator that enhances organizations' innovation performance (Ramakrishnan et al., 2012). Moreover, BDA has been shown to improve various aspects of the overall business system, including products, processes, infrastructure, and market segmentation, thereby enhancing the competitive advantage of organizations (Khan and Tao, 2022).

The study revealed a significant impact of IPF on PS (H6), consistent with previous research highlighting the influential role of innovation performance in project success (Ruoslahti, 2020; Shenhar and Dvir, 2013). These findings support the DCT, as innovation performance is considered a business capability that necessitates integrating knowledge across various capabilities within the innovation ecosystem. Collaborators foster creativity through the exchange and combination of different types of knowledge (Moller and Rajala, 2007). In a rapidly changing world characterized by evolving markets, products, and technology, knowledge dynamics as a valuable and irreplaceable resource (J. Barney, 1991) have become increasingly significant drivers of innovative performance.

Next, the results of the mediating analysis are discussed. The findings demonstrate BDA's positive and significant indirect effect on PS through knowledge sharing (H4), suggesting that BDA significantly influences how KS can enhance PS within IT organizations (Bag et al., 2020). These results align with the RBV and the DCT, as knowledge sharing relies on using BDA to improve PS and gain a competitive advantage (Constantiou and Kallinikos, 2015; Kharub et al., 2023).

Furthermore, IPF was found to significantly mediate the relationship between BDA and PS within IT companies (H7). This indicates that BDA significantly impacts how IPF can contribute to the project success of IT organizations (Jeble et al., 2018). These findings align with the resource-based view and the DCT, as innovation performance relies on utilizing BDA to improve PS and cultivate a sustainable competitive advantage (Norena-Chavez and Thalassinos, 2023).

5.2. Implications of the study

Following the pandemic, there is a strong rationale for IT companies to investigate the role of BDA, KS, and IPF in achieving project success. This recent study has several implications. Firstly, it argues that senior-level personnel in IT firms, who rely heavily on technology for survival and growth, should explore using BDA to foster KS and IPF, ultimately leading to PS. These leaders can serve as inspirations, encouraging employees to identify and embrace business opportunities. Furthermore, the study highlights the importance of evaluating BDA, knowledge exchange, and innovation performance when selecting top IT leaders. Governments can also support IT business development by providing entrepreneurship training programs emphasizing knowledge sharing, innovation performance, and creating an environment conducive to innovation, thereby enhancing project success.

In conclusion, the interplay between KS, PS, and BDA can significantly enhance PS and give organizations a competitive advantage. Theoretically, the findings of this study shed light on the contribution of BDA, KS, and IPF to project success, drawing on the RBV and DCT theoretical frameworks. This study advances research on the interconnectedness of BDA, KS, IPF, and PS. Moreover, it enhances our understanding of the factors influencing project success in the IT sector. Given the limited literature on the relationship between BDA and PS, this study fills a crucial gap and calls for further research. By exploring the role of BDA in facilitating KS and IPF in IT firms, this study provides valuable insights that can contribute to achieving favorable project outcomes. Understanding direct and indirect factors that can enhance project success enables firms to gain a competitive advantage. This study offers unique perspectives by examining the context of Peru's IT sector through the lenses of the RBV Theory and DCT. It enriches our understanding of project success in IT companies.

5.3. Limitations and future research directions

It is essential to acknowledge the limitations of this study. Firstly, the cross-sectional design employed in this study means that the data collected only represents a snapshot in time and cannot capture dynamic changes accurately. To address this limitation, future research could consider longitudinal data collection to more effectively examine causation and the dynamic impact mechanism. Secondly, it is worth noting that this study focused solely on Peru. Future research should include samples from different countries and sectors to enhance the generalizability of the findings. This would provide a broader perspective and allow a better understanding of the relationship between BDA, KS, IPF, and PS across various contexts.

Furthermore, future studies could explore additional mediating variables, such as entrepreneurial passion, knowledge management systems, and innovative team behavior. These variables may further elucidate the underlying mechanisms through which BDA influences PS. Additionally, future research may consider evaluating additional moderating variables, such as entrepreneurial leadership and intellectual capital. By examining the influence of these factors, a more comprehensive understanding of the complexities surrounding the relationship between BDA and PS can be obtained.

6. Conclusions

This study contributes a pioneering perspective on the interrelationship between BDA, PS, KS, and IPF (**Table 7**). The findings, revealing the indirect effect of BDA on project success through knowledge sharing and the mediating role of IPF, underscore the significance of data-driven strategies. This research bridges a critical gap in understanding the interconnected dynamics of BDA, knowledge sharing, innovation performance, and organizational success. By offering practical insights and guiding BDA integration and collaborative cultures, this study provides actionable implications for enhancing project management practices and sustained success.

Table 7. Conclusions.

Hypotheses	Results	Supporting literature
(H1) BDA > PS	Supported	(Jugdev et al., 2013; Lu and Ram, 2011; O'Driscoll, 2014)
(H2) BDA > KS	Supported	(Alavi et al., 2006; Gasik, 2011; Gold et al., 2001)
(H3) KS > PS	Supported	(Behl et al., 2023; Kharub et al., 2023)
(H5) BDA > IPF	Supported	(Lehrer et al., 2018; Y. Wang and Hajli, 2017)
(H6) IPF > PS	Supported	(Ruoslahti, 2020; Shenhar and Dvir, 2013)
(H4) BDA > KS > PS	Supported	(Bag et al., 2020; Kharub et al., 2023)
(H7) BDA > IPF > PS	Supported	(Jeble et al., 2018; Taguimdje et al., 2020)

Conflict of interest

There is no conflict of interest.

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