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Harnessing Big Data Analytics for Innovation Performance in Peruvian High-Tech SMEs: The Mediating Role of Team Entrepreneurial Passion

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Abstract. This study investigates the impact of Big Data Analytics (BDA) on Innovative Performance (IP) in small and medium-sized high-tech firms in Peru, focusing on the mediating role of team outcomes, namely Team Innovation Culture (TIC), Team Reflexivity (TR), and Team Entrepreneurial Passion (TEP). Drawing on the Resource-Based View Theory (RBV) and Social Learning Theory (SLT), the research analyzes data from 422 IT executives using PLS-SEM. The findings reveal a significant positive impact of BDA on IP and TEP, with TEP partially mediating the BDA-IP relationship. Surprisingly, TIC and TR do not mediate the BDA-IP relationship. The study contributes to the literature by highlighting the crucial role of BDA in fostering IP and the importance of team outcomes, particularly TEP, in this relationship. The findings offer valuable insights for managers seeking to harness BDA for enhancing innovation performance in high-tech SMEs.

Keywords: Big data Analytics, Innovative Performance, Team Innovation Culture, Team Reflexivity, Team Entrepreneurial Passion

1. Introduction

Big data analytics (BDA) has attracted substantial attention for its potential to significantly influence business decision-making processes (Awan et al., 2021). As a result, organizations are ramping up their engagement with BDA to derive insights that secure a competitive edge. According to Mikalef et al. (2020), businesses are increasingly adopting sophisticated data processing technologies and strategic decision-making frameworks to maintain this advantage in a rapidly changing market environment. Recently, there's been a surge in business interest in harnessing large datasets to improve critical performance indicators, such as project success rates, further driving the momentum towards BDA adoption (Lutfi et al., 2023). BDA has emerged as a recent focus of academic research, garnering interest from both scholars and industry professionals (Norena-Chavez & Thalassinos, 2023). Although consulting firms, media outlets, and individual case studies have produced numerous reports highlighting the value of BDA, these often lack robust empirical support (Chen et al., 2015). Research on BDA's competitive advantages is still in its early stages, with a clear understanding of how BDA investments translate into organizational benefits remaining elusive (Mikalef et al., 2019). While there has been a considerable emphasis on the psychological factors affecting IP, the technological aspects, particularly BDA's role, have received relatively less attention. Recent scholarly efforts have begun to explore BDA's critical role within the context of IP (Sun et al., 2020).

Existing studies have examined the impact of BDA on IP outcomes, including research by Niebel et al. (2019), Mikalef and Krogstie (2020), and Blackburn et al. (2017). This body of work has shown that BDA's influence on IP is indirect, a finding supported by studies from Xiao et al. (2020) and Bhatti et al. (2022). Despite these insights, there remains a significant gap in understanding the mechanisms by which BDA enhances IP. Current research has largely concentrated on BDA's role in boosting individual outcomes leading to improved IP. However, it is also crucial to explore how enhancements at the team level, as discussed in studies by Xu et al. (2023) and Bouschery et al. (2023), can drive innovation. Accordingly, this study investigates TR, TIC, and TEP as potential mediators of BDA's contribution to IP.

This study illuminates several underexplored aspects of the relationship between BDA and IP. It aims to bridge existing knowledge gaps by deepening our understanding of how BDA contributes to IP. Companies aiming for a sustainable competitive advantage must develop a blend of technological, human, financial, and intangible assets. While there has been a move towards a more holistic approach to BDA in some studies, the detailed mechanisms by which BDA influences IP still require further exploration. Recent research suggests that the impact of BDA on company performance is indirect, mediated by other corporate strategies (Mikalef et al., 2018). For the progression of both theory and practice, as well as to guide future research, it is crucial to determine how BDA's essential elements foster the development of TIC, TR, and TEP, thus improving IP. This need points to several areas within BDA, TIC, TR, TEP, and IP that remain unresolved in the literature.

Initially, interest in BDA has been increasing, yet the concept of BDA itself is still not fully developed (Mikalef et al., 2019). Research into BDA's impact on Innovation Performance (IP) has been limited (Khan & Tao, 2022). Significant studies, such as those by Sun et al. (2020) and Khan & Tao (2022), have investigated the relationship between BDA and IP. However, the academic community has not conclusively determined whether BDA directly enhances innovation performance (Muhammad et al., 2022), suggesting that the examination of BDA in the context of IP is far from complete. This underscores the urgent need for further research to clarify how BDA might influence IP and confirm its effects (Wang et al., 2023). More empirical research is required to understand the dissemination of BDA effects and the realization of benefits (Munir et al., 2021). While Sun et al. (2020) found that BDA significantly impacts the allocation of risk capital to enhance IP without serving as a mediator or moderator, Khan and Tao (2022) discovered that a Data-Driven Culture moderates the BDA-IP relationship. Nevertheless, they did not consider mediating variables that could illuminate the specific ways BDA impacts IP within the IT sector of developing countries. Therefore, examining the role of

Workforce Management Dynamics (WMD) capabilities in influencing organizational characteristics and their subsequent effect on IP is essential.

Second, while existing research has assessed the impact of BDA on team outcomes, such studies remain scarce. Iqbal et al. (2020) investigated how BDA uncovers hidden patterns, trends, and correlations, aiding teams in identifying new opportunities, market trends, and consumer preferences to spark innovative ideas. Furthermore, BDA employs data-driven evidence, critical analyses, exploration of alternatives, and the development of adaptive strategies, thereby enabling teams to make more informed and successful decisions (Agostini et al., 2023). Kache and Seuring (2017) pointed out that BDA equips teams with comprehensive and current information from a variety of data sources, facilitating well-informed decisions regarding market developments, customer behavior, and the competitive landscape. This, in turn, boosts their confidence in chasing business opportunities and fuels their enthusiasm for their ideas and their implementation. Therefore, there is a noticeable gap in research exploring how BDA can improve team outcomes in the context of IP.

Thirdly, the interaction between BDA and IP has been examined through various mediators in studies by Iqbal et al. (2020), Agostini et al. (2023), and Kache & Seuring (2017), raising questions about the direct influence of BDA on RI. To clarify how BDA impacts IP, this research identifies TIC, TR, and TEP as potential intermediaries in this dynamic. BDA is suggested to facilitate the development of TIC, TR, and TEP in numerous ways. BDA's capability to extract and analyze vast data sets for identifying patterns and trends enables organizations to enhance team outcomes, such as best practices, procedures, and methods, thus promoting innovation and efficiency across the organization (Babu et al., 2021). BDA serves as a critical instrument for organizations to foster TIC, TR, and TEP; through the analysis of extensive data, organizations can gain crucial insights and information, which support decision-making and guide the fostering of robust team outcomes (Khang et al., 2023).

TR, TIC and TEP are essential in contemporary business organizations, enhancing data-driven decision-making, innovation, adaptability, and securing a competitive advantage in an ever-evolving business landscape (Tindiwensi et al., 2023; Zhou et al., 2023; Zhu et al., 2023). These factors contribute significantly to organizational effectiveness, employee satisfaction, and sustained success. This study is grounded in the RBV and SLT. RBV, a strategic management framework, emphasizes the critical role of an organization's internal resources and capabilities in maintaining a competitive edge (Barney, 2001). It suggests that a company's competitive advantage is derived from its unique and valuable resources, which are difficult for competitors to replicate or acquire. Conversely, SLT, formulated by psychologist Albert Bandura, is a psychological framework highlighting the importance of observation, imitation, and social interaction in learning (Bandura, 1969). This theory proposes that individuals acquire new behaviors and knowledge by observing the actions and consequences experienced by others, especially in a social setting.

This study aims to address the identified gaps in team outcomes and contributes significantly in several ways. First, it broadens the limited research on the impact of BDA on IP, positioning it as a pioneering work to investigate BDA's role as a critical precursor to IP, especially within information technology firms. Second, given the scant research on BDA's influence on TIC, TR, and TEP, this study explores BDA's capacity as a major influencer of these elements. This investigation seeks to shed light on the potential relationship between BDA and these key organizational performance factors. Third, the study evaluates the mediating effects of TIC, TR, and TEP on the BDA-IP relationship, providing insights into the ways BDA might impact IP. This analysis forms the basis for a more detailed theoretical understanding of BDA's contribution to RI by elucidating these mediation processes. Lastly, by emphasizing BDA's role in bolstering RI through its effects on TIC, TR, and TEP, the research enriches the fields of the RBV and SLT, enhancing our understanding of how BDA integrates with these theoretical frameworks and its wider implications for organizational success.

The document is organized as follows: Section 2 reviews the literature and formulates hypotheses. Section 3 describes the study's design and research methodology. Section 4 presents the empirical findings. Section 5 discusses the results and their implications.

2. Literature review and hypothesis development

2.1. Big Data Analytics and Innovative Performance

The term "big data" has been in use since the 1990s, with some attributing its growing prominence to the contributions of John Mashey, a respected American computer scientist and entrepreneur. However, its initial application in the information field focused on techniques for data presentation (Cox & Ellsworth, 1997). In the early 2000s, the concept of "big data" in the context of management and business began to gain recognition. It was formally defined by Doug Laney, a Gartner analyst, as noted by Mariani et al. (2018). Since its inception, BDA has been the subject of considerable academic research spanning multiple disciplines, including information management, supply chain management, marketing, and financial management (Cox & Ellsworth, 1997). Nevertheless, large amounts of diverse data are required to generate relevant information. To achieve effectiveness, the field of data analytics requires the adoption of a comprehensive methodology covering stages such as data access, storage, analysis, and interpretation, ultimately aiming to extract meaningful and valuable insights (Mariani & Baggio, 2022).

The concept of IP refers to the effectiveness and outcomes of an organization's efforts in creating and implementing innovative concepts, products, procedures, services, or technologies (Abbas & Khan, 2023). This metric evaluates how much an organization's creative initiatives contribute to its overall achievement, growth, and competitive advantage (Borah et al., 2022). IP lacks a universally accepted definition and can vary depending on the industry and company objectives (Gomes et al., 2022). IP encompasses dimensions such as product, process, organizational, and market innovation (Yuan & Cao, 2022).

The use of BDA enables companies to collect and analyze extensive data from various sources (Batko & Ślęzak, 2022). BDA facilitates a deeper understanding of customer preferences, market trends, and emerging opportunities, empowering companies to identify unmet needs and enhance their IP (Zheng et al., 2022). BDA uncovers complex patterns and correlations beyond the capabilities of conventional methods, stimulating innovation in novel products, services, and procedures (Grover et al., 2018). By enabling real-time feedback from customers and stakeholders, BDA accelerates iterative adaptations, enabling companies to respond quickly to market changes and foster innovation (Babu et al., 2021). The relationship between BDA and IP can be explained by considering the RBV. In the RBV, BDA and IP are strategically linked through the use of data-based capabilities as valuable and unique resources (Dubey et al., 2019). BDA helps companies collect, analyze, and interpret large amounts of data, creating a unique foundation of creative resources and enhancing IP (Awan et al., 2019). Based on these arguments, the following hypothesis is proposed:

H1: There is a significant and positive impact of BDA on IP.

2.2. Mediating Role of the Team Innovation Culture

TIC refers to the dynamic process by which teams generate, adopt, implement, and integrate new ideas into their operations (Hsu et al., 2022). According to Amabile (1988), establishing a culture of innovation in a team depends on the combined influence of domain-relevant skills, creativity-relevant capabilities, and task motivation. By providing valuable insights from diverse data sources, the BDA fosters informed decision making that stimulates innovative thinking, enabling teams to develop creative and effective solutions based on data-backed evidence rather than assumptions (Saggi & Jain, 2018). By analyzing large data sets, BDA reveals hidden patterns, trends, and correlations, empowering teams to recognize emerging opportunities, market trends, and consumer preferences, which drives the generation of novel and innovative ideas (Iqbal et al., 2020). By providing teams with a deep understanding of complex challenges, BDA generates collaborative brainstorming sessions among diverse team members, leading to innovative solutions derived from fresh perspectives (Bellandi, 2022). The impact of BDA on TIC can be explained in light of SLT. According to TAS, people learn by observing others. The BDA provides a platform for sharing and disseminating ideas derived from data analysis in the context of teams (Elia et al., 2022). Team members can observe how data-driven ideas lead to innovative solutions, fostering a culture where learning from the successes and experiences of others is an integral part of innovation (O'Neil et al., 2023).A strong TIC facilitates an environment where diverse perspectives are valued and encourages team members to share their ideas freely, resulting in a broader set of innovative concepts (Nguyen et al., 2022). When teams have an innovation culture that encourages the acceptance and promotion of carefully evaluated risks, team members tend to actively pursue unconventional and potentially Transformational ideas (Mannucci & Shalley, 2022). This innovation culture strongly emphasizes collaboration and open communication among team members, enabling them to work together on projects, exchange valuable ideas, and jointly improve the overall quality of innovation outcomes (Feng et al., 2022).

The impact of ICE on IP can be explained in light of the Resource-Based Perspective (RBP). The TIC nurtures a diverse set of skilled and creative individuals with unique knowledge and skills, serving as a distinctive asset that amplifies the team's ability to generate innovative ideas and effectively implement novel solutions (Pang & Plucker, 2012). A firmly embedded innovation culture shapes the team's processes and routines, incorporating innovation as a systematic and integral aspect of their efforts, which facilitates the constant generation, refinement, and implementation of innovative ideas (Magistretti et al., 2021).

Based on these arguments, the following hypotheses are proposed:

H2: The BDA has a positive and significant impact on TIC.

H3: There is a significant impact of TIC on IR.

Data-driven ideas from the BDA can foster collaboration in the team (Bellandi, 2022), and the open communication and willingness of the TIC to explore ideas can leverage this knowledge, fostering innovative idea generation and problem solving (Mannucci & Shalley, 2022). Based on these arguments, The following hypothesis is put forward:

H4: TIC mediates the relationship between BDA and IR.

2.3. Mediating Role of Team reflexivity

TR is based on the idea that the environment in which a team operates is dynamic and subject to continuous change. Therefore, it requires constant reflection and careful consideration to evaluate recent events and identify the most effective approach (Hoegl & Parboteeah, 2006). By providing comprehensive and up-to-date insights derived from large data sets, the BDA enables teams to better understand their performance, increasing their awareness of areas of strength, weakness, and potential opportunities for improvement (Dwivedi et al., 2021). The BDA is instrumental in promoting informed decision making within teams by utilizing data-backed evidence, which triggers a growing assessment, exploration of alternatives, and development of adaptive strategies, ultimately enabling teams to achieve more deliberate and successful outcomes (Agostini et al., 2023). The impact of DBA on TR can be explained in light of SLT. The DBA enables teams to gain valuable insights through data analysis, fostering a culture of reflection as team members observe, analyze, and learn from these insights, leading to behavior modification (Belhadi et al., 2019). The DBA models reflective behaviors by showing how data analysis produces valuable insights and facilitates improvements, which, when observed by team members, encourages the adoption of similar techniques and cultivates an environment conducive to continuous learning and reflection (Kache & Seuring, 2017).

TR fosters an environment of open communication and dynamic discussion, where the exchange of ideas and viewpoints promotes creative thinking and brainstorming, resulting in a wider range of unique concepts (Tan et al., 2023). Teams' adept at reflexivity exhibits strong abilities to critically analyze challenges and identify possible solutions, employing this analytical approach to effectively address complex problems, which fosters the generation of innovative resolutions and positively impacts IP (Schippers et al., 2015). ER nurtures a shared vision and understanding within a team, enhancing cooperation, reducing misunderstandings, and fostering a cohesive environment in TR among members to pursue common innovative goals (Vashdi et al., 2007). The relationship between TR and IP can be explained in light of the Resource-Based Perspective (RBP). The RBP emphasizes team knowledge and skills, dynamic capabilities, resource mix, organizational culture, innovation-oriented routines, strategic alignment, and innovativeness to explain how TR affects IP (Dovbischuk, 2022); reflexivity helps the team to efficiently use innovation resources, improving Innovation Performance. TR fosters continuous improvement, adaptation and learning from failures, directly improving innovation and the team's ability to generate and implement novel ideas, which influences IP (Farnese & Livi, 2016).

Based on the arguments presented, the following is proposed:

H5: The DBA has a positive and significant impact on the TR.

H6: There is a significant impact of TR on IP.

Teams possessing reflective qualities demonstrate a high level of competence in the critical analysis of information (Agostini et al., 2023). Collaborative efforts of team members enable analysis and interpretation of insights gained from the DBA, thus fostering a deeper understanding of data patterns, trends, and potential avenues for IP (Dovbischuk, 2022).

H7: The TR measured in the relationship between the DBA and the IP.

2.4. The Mediating Role of Team Entrepreneurial Passion

According to Cardon et al. (2009), entrepreneurial passion refers to a consciously attainable and highly favorable emotion that arises from an entrepreneur's engagement in activities that hold personal meaning and relevance. BDA provides teams with extensive and up-to-date information obtained from a wide range of data sources, assisting teams in making informed decisions about market development, customer behavior, and the competitive landscape. By offering accurate and current information to teams, their confidence in pursuing entrepreneurial opportunities is enhanced, stimulating their enthusiasm by reinforcing their belief in the potential of their ideas and their ability to execute them efficiently.

The impact of BDA on TEP can be explained in the light of SLT. SLT offers valuable insights into how exposure to successful instances of BDA implementation by other teams and peers can influence the formation and maintenance of TEP. It provides a framework for understanding the influence of BDA on TEP through the examination of favorable outcomes, the development of confidence, the promotion of collaborative efforts, the shaping of risk perceptions, and the encouragement of innovative behaviors. SLT explains how BDA affects TEP by analyzing positive outcomes, strengthening confidence, fostering collaboration, shaping risk perceptions, and promoting innovation.

The relationship between TEP and IP can be explained in the light of RBV. Firstly, TEP can inspire team members to be more innovative and creative, as when they are enthusiastic about their work, they are more likely to generate new ideas and problem-solving strategies (Romani-Torres & Norena-Chavez, 2023). Secondly, TEP can help team members overcome challenges and obstacles, as when they are dedicated to their goals, they are more likely to persevere despite setbacks. Thirdly, TEP can foster a positive and conducive environment for innovation, as when team members feel encouraged and supported, they are more likely to take risks and try new things.

Based on these arguments, the following hypotheses are proposed:

H8: BDA has a positive and significant impact on TEP.

H9: There is a significant impact of TEP on IP.

TEP, characterized by fervent dedication to innovation, synergistically amplifies motivation, commitment, and involvement among team members when integrated with BDA, resulting in the effective utilization of BDA ideas and potentially driving IP. Based on these arguments, the following hypothesis is proposed:

H10: TEP mediates the relationship between BDA and IP.

The proposed model is as follows (Figure 1).

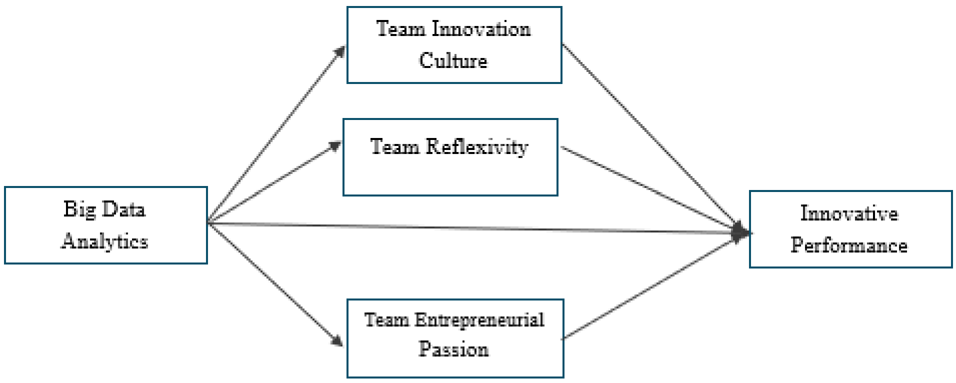

Fig.1: Research framework

3. The Research Methodology

3.1. Study areas and research design.

The methodology for gathering data in this research involved conducting in-person sessions in Peru with seasoned IT executives, specifically targeting the technology and services industry within the nation. Participants were selected based on their roles as executives of small and medium-sized enterprises (SMEs) with at least 5 years of experience in the IT sector. The sample comprised 422 IT executives from regions where the IT sector is most concentrated in Peru, reflecting the distribution of IT companies across the country: Lima (76%), Arequipa (4%), La Libertad (Trujillo) (1%), and the Callao province (4%). This distribution mirrors the fact that 85% of IT companies in Peru are located in these four areas. Before participating, each individual was provided with comprehensive details regarding the goals and extent of the study. They formally agreed to take part by signing consent forms, thereby giving their informed consent. It was emphasized to participants that the data collected would be solely for research purposes and not for commercial use, with strict adherence to data collection protocols.

At the start of the survey, an additional precaution was taken to brief participants about the anonymity and confidentiality of their data, further safeguarding their rights and privacy. A brief survey invitation was also given, highlighting the aim of the study, any potential risks involved, and the questions to be asked. For the purposes of the research, each respondent was considered a separate entity, a perspective that was maintained in the subsequent analysis of the data. The research followed ethical standards and was rigorously reviewed by an ethics committee to guarantee the respectful and ethical involvement of all participants.

In this research, a convenience sampling method, which is non-random, was utilized, acknowledging the potential biases inherent in such a selection process. The data collection period spanned from November to December 2022. Out of 500 questionnaires that were distributed, 450 were returned, yielding a response rate of 90%. Of these, 422 responses were considered valid for analysis. The in-person method of conducting surveys ensured high participation and engagement, but it also introduced potential biases related to the convenience sampling method and the geographical concentration of participants. Such biases could influence the generalizability of the findings, as the sample may not fully represent the diversity within Peru's IT sector. Detailed demographic information about the respondents is displayed in Table 1.

Table 1. Demographic information

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

3.2. Measures

The survey items were sourced from reliable and previously validated instruments. To ensure a high-quality translation, each questionnaire item underwent both direct and reverse translation processes. Additionally, to mitigate potential language and comprehension issues, a pilot test was conducted, involving the participation of five IT CEOs. Their feedback was incorporated to refine the questionnaire, ensuring its validity and accuracy. Each item was evaluated on a 5-point Likert scale, where 1 represented "strongly disagree," and 5 denoted "strongly agree."

4. Data Analysis and Results

4.1. Measurement Model Assessment

Data analysis was conducted using Smart-PLS 4.0.9.5 (Ringle et al., 2022), with the model evaluation focusing on the assessment of measurement and structural models. The research employed Partial Least Squares Structural Equation Modeling (PLS-SEM) as the analytical method, chosen to align with the study's focus on intricate relationships among variables and meet research objectives (Hair et al., 2019). A copyright license for PLS-SEM was obtained, allowing the analysis of complex models with multiple latent constructs a fitting choice for addressing the challenges inherent in the study (Hair et al., 2022).

4.2. Measurement Model Assessment

The measurement model underwent tests for the reliability of constructions, convergent validity, and discriminant validity in the PLS-SEM analysis. Initially, factor loadings were assessed. While an ideal loading is considered 0.7, social science research commonly encounters factor loadings below 0.7.

Before discarding indicators, the study examined composite reliability, content, and convergent validity. Following Hair et al.'s (2016) suggestion, items with factor loadings in the range of 0.40 to 0.70 were excluded only if their removal improved composite reliability or average variance extracted (AVE) above recommended levels. Some items had loadings between 0.40 and 0.70, but only one item, TEPI1, had loadings below recommendations, and it was excluded from the analysis, given satisfactory reliability and validity statistics of TEPD. Additionally, an item from TIC (TIC1) with a loading of 0.576 was removed, as its exclusion improved AVE. Construct reliability, measured by Cronbach's alpha and composite reliability, demonstrated that all research constructs exceeded the 0.70 threshold, proving reliable. Convergent validity was assessed through AVE, surpassing the 0.500 value, indicating acceptable convergent validity. The results of model reliability and validity are presented in Table 2. Discriminant validity was confirmed by comparing latent variable correlations with the square root of AVE and the heterotrait–monotrait correlation, all below 0.85. Results of discriminant validity are presented in Tables 3 and 4.

Table 2. Construct reliability and validity.

Construct	Item	Outer loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Big Data Analysis					
(BDA)	BDA1	0.798	0.764	0.849	0.585
	BDA2	0.715			
	BDA3	0.774			
	BDA4	0.77			
Innovation Performance	IP1	0.796	0.700	0.818	0.532
	IP2	0.741			
	IP3	0.791			
	IP4	0.567			
Team Entrepreneurial	TEPD1	0.793	0.794	0.842	0.571
Passion/Develop-ment	TEPD2	0.763			
(TEPD)	TEPD3	0.73			
	TEPD4	0.736			
	TEPI2	0.718	0.758	0.842	0.574
	TEPI3	0.82			
	TEPI4	0.816			
Team Entrepreneurial	TEPI5	0.664			
Passion/Innovation	TIC2	0.814	0.836	0.883	0.601
(TEPI)	TIC3	0.76			

	TIC4	0.784			
Team Innovation	TIC5	0.762			
Culture (TIC)	TIC6	0.755	0.839	0.883	0.603
Team Reflexivity (TR)	TR1	0.759			
	TR2	0.726			
	TR3	0.785			
	TR4	0.833			
	TR5	0.774			

Table 3. Fornell-Larcker Criterion

	BDA	TR	TEPD	TEPI	TIC	IP
BDA	0.765					
TR	0.541	0.730				
TEPD	0.154	0.376	0.756			
TEPI	0.381	0.438	0.418	0.757		
TIC	0.202	0.332	0.506	0.480	0.775	
IP	0.202	0.322	0.557	0.405	0.748	0.776

Table 4. Heterotrait-monotrait ratio (HTMT)

	BDA	TR	TEPD	TEPI	TIC	IP
BDA						
TR	0.722					
TEPD	0.174	0.428				
TEPI	0.466	0.571	0.521			
TIC	0.247	0.413	0.623	0.629		
IP	0.243	0.385	0.707	0.546	0.892	

4.3. Higher-Order Constructs Validation (TEP)

TEP formation stems from development and invention processes. The presence of multicollinearity was assessed using Variance Inflation Factor (VIF). Values below 5, according to Hair et al. (2022), indicate the absence of multicollinearity, confirmed in this study as all VIF values were below this threshold, as shown in Table 5. Subsequently, the statistical significance and relevance of external weighting coefficients were examined, and according to Sarstedt et al. (2019), the external weighting coefficients of team entrepreneurial enthusiasm indicators were significant and robust, supporting the validation of TEP. Results of higher-order structures are presented in Table 5.

Table 5. Higher order constructs

	VIF	Outer Weights	T statistics	P values	Outer loadings	T statistics	p values
TEPD -> TEP	1.211	0.3000	2.905	0.002	0.649	7.865	0.000
TEPI -> TEP	1.211	0.837	11.659	0.000	0.962	34.894	0.000

4.4. Structural Model

Next, the structural model is evaluated to support proposed relationships. Considering R2, results reveal that a 4.1% change in TR, a 4.0% change in TIC, and a 13.3% change in TEP can be attributed to BDA. The 39.2% change in IP can be attributed to BDA, TR, TIC, and TEP. Additionally, Q2 establishes predictive relevance, with a Q2 above 0 indicating predictive relevance. Results demonstrate significance in predicting constructs. The results of the structural model evaluation and hypothesis testing are as follows and refer to Table 6).

BDA´s Direct Impact on IP (H1): The results supported the hypothesis that BDA has a direct positive effect on IP (β =.421, t = 9.397, p =.000), indicating that BDA is a significant predictor of IP.

BDA´s Direct Impact on TIC (H2) and TR (H5): Both hypotheses were supported, showing that BDA positively affects TIC (β =.201, t = 4.037, p =.000), and TR (β =.202, t = 4.269, p =.000). This suggests that BDA contributes to enhancing both the team innovation culture and reflexivity of teams.

TIC´s and TR´s Impact on IP (H3 and H6): The hypotheses that TIC and TR would affect IP were not supported, as TIC did not significantly affect IP (β =.053, t = .648, p =.258) and neither did TR (β =.063, t = 0.940, p =.174). This indicates that while BDA influences TIC and TR, these do not directly translate into improved IP.

BDA´s Impact on TEP (H8) and TEP´s Impact on IP (H9): The results supported these hypotheses, showing that BDA positively affects TEP (β =.365, t = 6.731, p =.000) and that TEP, in turn, positively affects IP (β =.263, t = 3.924, p =.000). This highlights the importance of entrepreneurial passion within teams as a channel through which BDA influences IP.

Table 6. Hypotheses results, coefficient of determination and predictive relevance

Hipótesis	*Relation*	*β*	*σ*	*T*	*P values*	Decision
H1	BDA -> IP	0.421	0.045	9.397	0.000	Accepted
H2	BDA -> TIC	0.201	0.050	4.037	0.000	Accepted
H3	TIC->IP	0.053	0.082	0.648	0.258	Rejected
H5	BDA -> TR	0.202	0.047	4.269	0.000	Accepted
H6	TR ->IP	0.063	0.067	0.940	0.174	Rejected
H8	BDA -> TEP	0.365	0.054	6.731	0.000	Accepted

H9	TEP -> IP	0.263	0.067	3.924	0.000	Accepted
		R^2	Q^2			
	IP	0.392	0.284			
	TEP	0.133	0.123			
	TIC	0.04	0.034			
	TR	0.041	0.032			

4.5. Mediation Analysis

TIC as a Mediator (H4): TIC was not found to mediate the relationship between BDA and IP (β = .011, t = 0.610, p = .271), indicating that TIC does not play a mediating role in this context.
TR as a Mediator (H7): Similarly, TR did not mediate the relationship between BDA and IP (β = .013, t = 0.893, p = .186), suggesting that TR does not serve as a pathway for the BDA-IP relationship.
TEP as a Mediator (H10): In contrast, TEP was found to partially mediate the relationship between BDA and IP (β = .096, t = 3.628, p = .000), confirming that TEP is a significant mediator that explains how BDA contributes to IP. See Table 7.

Table 7. Mediation analysis

Total Effect	*β*	*σ*	*T*	*P values*	*Indirect Effec*	*β*	*σ*	*T*	*p*	Decisión
BDA -> IP	0.541	0.038	14.064	0.000	H4: BDA -> TIC ->IP	0.011	0.017	0.61	0.271	Rejected
					H7: BDA -> TR -> IP	0.013	0.014	0.893	0.186	Rejected
					H10: BDA -> TEP -> IP	0.096	0.026	3.628	0.000	Accepted

5. Discussion

All papers This study explores how BDA indirectly influences innovation performance (IP) through TR, TIC, and TEP. Our findings align with previous research (Mariani & Baggio, 2022; Zheng et al., 2022), affirming that BDA significantly enhances IP (H1). This supports the Resource-Based View (PBR) theory, highlighting BDA as a vital, rare, and irreplaceable resource that enables companies to enhance IP by providing unique insights, improving efficiency, and accelerating product development. This research confirms the significant impact of BDA on TIC (H2), consistent with previous studies (Iqbal et al., 2020; Saggi & Jain, 2018), supporting the Social Learning Theory. It demonstrates that an organization's team can learn from successes and failures driven by BDA, ultimately enhancing their IP. The study established a significant positive relationship between TIC and IP (H3), reinforcing previous findings indicating the substantial impact of TIC on IP (Mannucci & Shalley, 2022; Feng et al., 2022). These results align with the PBR theory, suggesting that TIC nurtures a diverse group of talented and creative individuals with unique skills and knowledge, expanding the team's capacity to generate innovative ideas and implement novel solutions.

The research revealed that BDA significantly influences TR (H5), corroborating existing studies that identified a substantial impact of BDA on TR (Agostini et al., 2023). TR is strongly influenced by BDA's emphasis on observational learning, modeling, and social norms. In TR, team members observe and learn from data-driven decision-making processes, adjust their behavior based on others' performance with data analysis, and develop norms valuing tacit knowledge based on data (Belhadi et al., 2019). BDA models reflective behaviors by demonstrating how it produces valuable information and improvements, encouraging team members to adopt similar methods and creating an environment of continuous learning and reflection (Kache & Seuring, 2017). The study found that TR does not affect IP (H6). This contradicts existing research (Tan et al., 2023; Schippers et al., 2015). Additionally, the study contradicts the PBR theory (why this might be the possible reason). The contradiction may arise when reflective processes do not generate concrete, valuable, and difficult-to-imitate resources necessary for continuous innovation. Accessibility to resources, dynamic capabilities, external influences, resource complementarity, organizational culture, and leadership influence TR performance beyond the PBR theory's focus on resource-based advantages (Martin-Hidalgo & Pérez-Luño, 2022). The research revealed that BDA significantly influences TEP (H8), corroborating existing studies that identified a substantial impact of BDA on TEP (Zhang et al., 2022; Katoch et al., 2023). The results support the Social Learning Theory. Social Learning Theory illustrates how BDA enhances TEP by facilitating observational learning, modeling data-driven behaviors, and cultivating an entrepreneurial culture within teams. The study found that TEP significantly influences IP (H9). The results support the PBR theory that BDA can function as a valuable, scarce, and irreplaceable resource, empowering companies to drive IP by providing unique insights, improving efficiency, and facilitating more focused and rapid product development (Mostafiz et al., 2022).

The results reveal that TIC does not significantly mediate the relationship between BDA and IP (H4). Additionally, the results show that TR does not significantly mediate the relationship between BDA and IP (H7). It was discovered that TEP plays a mediating role in the relationship between BDA and IP (H10). PBR and Social Learning Theory can offer theoretical support for the mediating function of TEP in the interaction between BDA and IP. These theoretical frameworks provide a conceptual foundation for understanding how BDA, as a valuable resource, interacts with TEP, resulting in improved innovation performance. BDA and TEP can provide innovation benefits to companies, according to PBR. Social Learning Theory emphasizes that teams can learn from each other through social contact, and TEP can help transfer and use BDA knowledge to enhance innovation performance. The PBR focus on resource dynamics and the Social Learning Theory's emphasis on team-based social learning promote the mediating role of TEP in the interaction between BDA and innovation (Mariani & Wamba, 2020).

6. Implication of the Study

6.1. Theoretical Implications

This study contributes to the theoretical understanding of BDA within the framework of the RBV and SLT theory, particularly in the context of IP in information technology projects. By examining the mediating roles of TIC, TR, and TEP in the relationship between BDA and IP, our research offers several theoretical advancements.

The RBV posits that a firm's competitive advantage is derived from its unique resources and capabilities. Our findings suggest that BDA represents a strategic resource that can enhance a firm's innovation performance, aligning with the RBV's emphasis on the importance of unique resources. Specifically, the positive impact of BDA on TEP underscores the value of technological resources in fostering an entrepreneurial spirit within teams, which in turn, contributes to innovation (Lutfi et al., 2023). This extends the RBV by highlighting the role of digital resources, such as BDA, as critical components of a firm's resource portfolio that can drive competitive advantage through enhanced innovation performance (Behl et al. (2022).

In addition, according to SLT, learning occurs within a social context through observation, imitation, and modeling. Our study reveals that BDA facilitates a learning environment that promotes team reflexivity and innovation capability, which are crucial for innovation performance. The mediation effect of TEP between BDA and IP illustrates how social learning mechanisms, facilitated by BDA, can lead to improved innovation outcomes. This finding enriches the SLT by demonstrating how technology-enabled learning environments can enhance the innovative capacity of teams in the IT sector.

6.2. Practical Implications

The findings of this research have significant implications for a broad range of stakeholders, including project managers, IT managers, project coordinators, and policymakers, who are interested in achieving better project performance, especially TEP, through the implementation of BDA. For Managers to leverage BDA for enhancing IP, managers should focus on developing and nurturing an entrepreneurial culture within teams. Investing in BDA technologies and training can foster a conducive environment for innovation, where team members feel empowered to experiment and learn from both successes and failures. For Policymakers, policies aimed at promoting the adoption of BDA in the IT sector should consider supporting initiatives that enhance team dynamics and entrepreneurial passion. This could include funding for BDA training programs and incentives for companies that demonstrate innovative uses of BDA (Ahmed et al., 2022).

7. Conclusions

This research analyzed the potential impact of BDA on IP among high-tech SMEs in Peru, with a particular emphasis on how team dynamics such as TIC, TR, and TEP play intermediary roles. The results underscore BDA's considerable positive effect on both IP and TEP, noting that TEP serves as a partial intermediary in the correlation between BDA and IP. Interestingly, neither TIC nor TR were found to act as mediators in this relationship.

This research contributes significantly to existing literature in several ways. Firstly, it identifies BDA as an essential precursor for enhancing IP, especially within the realm of high-tech SMEs. Secondly, it sheds light on the mediating influence of TEP on the link between BDA and IP, highlighting the critical role of cultivating entrepreneurial passion in teams to effectively utilize BDA in driving innovation. Lastly, the study broadens the Resource-Based View (RBV) and Social Learning Theory (SLT) by illustrating the interaction between BDA as a strategic resource and team dynamics in fostering innovation performance.

8. Limitations and Future Directions

Although this study provides valuable information, it is crucial to acknowledge its inherent limitations. The cross-sectional nature of this study constrains the possibility of establishing causal relationships, while its concentration on a single industry and national setting may restrict the broader applicability of its conclusions. Future investigations should adopt longitudinal approaches, delve into more mediating and moderating factors, and confirm these outcomes in different environments.

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Zhu, X., Yang, S., & Kromidha, E. (2023). The emergence of team entrepreneurial passion from team helping: An affective events theory perspective. International Small Business Journal, 41(3), 269-297.Table 1. Demographic information.