International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(12s) 2026 pp. 510-526
https://doi.org/10.70917/ijcisim-2026-3389
Article

Enhancing Organizational Performance through Big Data Analytics: The Interplay of Talent, Innovation, and Agility in IT Services

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Abstract: This investigation investigates the manner in which the use of Big Data Analytics Capabilities (BDAC) impacts organisational effectiveness in the information technology (IT) services industry, considering into thought the mediation responsibilities during talent capability, innovation, ambidexterity, and agility in addition to the modifying responsibilities of information circulation, alignment with strategy, along with fluctuations in the environment. This investigation expands further isolated analysis of relationships through providing an extensive as well as contextual dependant comprehension of BDAC-driven organisational achievement. To evaluate the effect of BDAC findings on organisational efficiency as well as evaluate the moderating and mediation functions of specific organisation components within the Indian information technology services sector. Utilising data collected from 650 employees in information technology in the nation of India, a conceptual framework that utilises information concepts as well as the changing abilities perspective was developed as well as experimentally verified with Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings indicate that BDAC significantly improves talent capacity, innovation, ambidexterity, and agility, among other things which enhance organisational effectiveness when considering of all the operational, financial, as well as environmental factors. Knowledge flow positively moderates the relationship between innovation and performance, while strategic alignment strengthens the link between dynamic talent capabilities and performance. Environmental turbulence intensifies the relationship between agility and performance.
Keywords: Big Data Analytics; Talent capability; Innovation; Ambidexterity; Agility; Organizational Performance

1. Introduction

Enterprises increasingly rely on analytics for strategic decisions in today's economy. Data analytics enables exploring possibilities, optimizing processes, meeting customer needs, forecasting behavior, and restructuring strategies (Ceipek et al., 2021; Kraus et al., 2022b). Digitization allows businesses to generate profit and enhance competitiveness in markets (Bertello et al. 2021). Technology adoption is crucial for entities comprising over 9% of EU businesses that are vital to the global economy. Evidence shows businesses with higher technological competence engage more in technology initiatives. The decision-making process as well as operational effectiveness increasingly depends upon BDA (Sharma et al., 2023; Li et al., 2021; Ye et al., 2023; Zhou et al., 2023). Many organisations finding it challenging to achieve information-driven perspective notwithstanding substantial investments. The following raises questions about the significance as well as economic feasibility of statistical data (Dubey et al., 2019) and additionally whether or not employees work able to effectively handling BDA technology (Sun, 2020).

The significance of the BDAC in organisational technological change has been repeatedly shown by investigation (Wamba et al. 2017; Bresciani et al. 2021; Volberda et al. 2021). On the other hand, there are still some concerns regarding the implementation of the BDAC, particularly regarding regard to the effect technological advances on organisational efficiency (Firk, 2022). Study concentrates on organizational modifications instead of BDA's capabilities for innovations (Brand et al., 2021; Zareravasan, 2023). Organisations have to consider advances in technology as well as creative abilities into consideration with the objective to enhance BDAC efficiency. Research studies on SMEs continue to be scarce, notwithstanding studies focusing on larger companies (Maroufkhani et al., 2019; Perdana et al., 2022a, 2022b). Although adopting the digital age, SMEs are facing difficulties concerning BDA as well as creative thinking (Bertello et al., 2021). When less developed countries, innovation is affected by financial limitations (El Telbany et al., 2020). Considering BDA and research on innovation mainly emphasise on IT, additional research throughout businesses must be undertaken (Upadhyay and Kumar, 2020).

Organisations may transform information expertise towards organisational planning with the implementation of operations skills. Though BDAC provides methods to analyse evaluating data, its effectiveness depends on companies' executive, managerial, as well as sales procedural abilities (Akter et al., 2016). Integrating management and analytical abilities promotes making decisions, and this improves effectiveness (Gunasekaran et al., 2017; Mikalef et al., 2018). Functioning ability enhances BDAC's impact on organizational success. PLS-SEM analysis, suitable for complex structures in digital transformation studies, examined relationships between organizational effectiveness, operating capabilities, and BDAC. This study shows BDAC and operational capabilities' effects on organizational performance. This study explores BDAC's technological, managerial, and social components' impact on organizational performance across operational, financial, and environmental dimensions. It examines how functional capabilities, including human resource expertise, innovation capacity, organizational ambidexterity, and agility, mediate this relationship. The study analyzes knowledge flow and strategic alignment's role in innovation processes and execution effectiveness, while evaluating how technological and market turbulence influence the relationship between BDAC, functional competence, and organizational performance. In this respect, this study aims to outline the following research aims towards a narrow and meaningful analysis:

- RQ1: What are the functional antecedents that lead to strategic organizational performance in BDAC-invested organizations?
- RQ2: Are other functional capabilities, including TC, innovation capability, firm ambidexterity, firm agility, dynamic TC, knowledge flow, or environmental turbulence, involved in this association?

The investigation study has been divided among major components. During the introductory section, an in-depth review of the research available is offered to determine the current state of understanding concerning BDAC and its connection with talent capability, innovation, ambidexterity, agility, and organisational effectiveness. The partial least-squares structural equation modelling (PLS-SEM) comprises one of the several various sampling, gathering information, as well as analysis of information methodologies offered through the method being used. The results have of the collected information investigation, comprising the evaluation of the method of measurement as well as hypotheses evaluation, will be discussed in the findings component. The findings are considered with regard towards the prevailing theories as well as previous findings from empirical studies. The result continues through highlighting the most significant results, limitations, as well as recommendations regarding further investigation in this field of study.

In the past few years, an enormous amount of investigation have been conducted on how applying analytical Big Data Capabilities (BDAC) impacts managerial abilities such as innovation, flexibility, and productivity (e.g., Akter et al., 2016). Nevertheless, these connections have primarily been investigated independently. Together a consequence, nothing is known regarding how these abilities operate within a cohesive unit for enhancing the performance of organisations.

For the purpose to get around this drawback, the present research constructs a multifaceted process-driven system that concurrently examines at historical influences (knowledge flow, strategic alignment, and environmental turbulence) as well several mediation mechanisms (talent capability, innovation, ambidexterity, and agility). While doing so, the investigation provides a contextual and configurational understanding underlying BDAC-enabled performance.

2. Literature Review.

2.1. BDA and Talent Capability (TC)

Analytics professionals' capability refers to performing specialized tasks in big data settings by integrating analytical capabilities with skills and knowledge (Wu et al., 2024). Big data analytics professionals transform raw data into business insights and report findings to domain professionals for informed decisions (Qaffas et al., 2022). Data-driven decisions increasingly influence workforce strategies, making big data's role more strategic. Organizations recognize the need to adapt statistical concepts for big data analytics as data scientists' importance grows (Khalil and Belitski, 2020). Complex data analysis requires advanced technical skills; thus, professionals with current technological expertise are best positioned to handle big data. As firms increasingly use data strategically, human capital becomes crucial.

- H1A: BDAC has a significant positive impact on talent/HR capability

2.2 BDAC and Innovation Capabilities

The impact of Big Data Analytics, or BDA, on method, products, technological, and modularity innovation have been emphasised throughout recent studies (Caputo et al., 2016; George and Lin, 2017; Ransbotham and Kiron, 2017; Trabucchi and Buganza, 2019). Through enabling companies to evolve into focused on customers through driven by data, BDA encourages innovative thinking as well as modification of business models (Del Vecchio et al., 2018; Trabucchi et al., 2018). The companies may capitalise on consumption of data to establish strategies as well as models for operation by utilising data gathered through sensor as well as technological advances (Trabucchi and Buganza, 2019). Companies like IBM, Google, and Airbnb, and Uber can be considered illustrations of the way analytical skills can result in information-driven technological advances in business operations, products, including products. Nevertheless BDA doesn't seem to commonly employed as a tactical instrument for effective innovation (Johnson et al., 2017).

- H1B: BDAC positively impacts innovation capabilities

2.3 BDAC and Firm Ambidexterity

The entire world has grown increasingly interconnected mainly because of advances in technology for communication and information, particularly large-scale data generation (Ferraris et al., 2019). Companies have to employ environmentally conscious methods of management for strategic choices if they are to achieve an edge over their competitors (Caputo et al., 2021), leading to the need for the establishment of BDACs. Material things, human abilities, as well as other than physical products comprise the BDAC (Mikalef et al., 2018). Interpersonal abilities associated with BDAC constitute instances of assets that are not physical (Aljumah et al., 2021). The key component of the present research is the perspective of dynamic capabilities (DCV), that focuses at the ability of an organization for adaptation via asset coordinating and procedure changes (Teece et al., 1997). The business processes are connected to the BDAC's adaptive abilities (Teece, 2018). Financial institutions can discover opportunities by altering procedures and resources for improved data utilization (Mikalef et al., 2018; Aljumah et al., 2021).

- H1C: BDAC are positively related to a firm's ambidexterity

2.4 BDAC and Firm Agility

Organizations view BDA as a strategic tool to handle technological changes and analytics accessibility. The growth of Internet and social media has led to increased data generation (Liu et al., 2016). Companies use customer relationship management systems to record contacts and build longitudinal data. BDAC helps firms predict market dynamics and make data-driven decisions (Hyun et al., 2020; Mandal, 2018; Zhou et al., 2019). Real-time data access enables companies to monitor competitors and evaluate technological trends and customer preferences (Lu and Ramamurthy, 2011). Through examining this relationship through a combined structure that includes multiple complementary abilities including contextual variables, this investigation improves on previous research (Cheng et al., 2020; Li et al., 2020). Analytics-driven adaptability enhances operational agility in dynamic markets (Ghasemaghaei et al. 2017).

- H1D: BDAC are positively related to a firm's agility

2.5 Talent Capabilities and Organization Performance

From the perspective of dynamic capabilities, skilled employees facilitate positive financial performance (Lutfi et al., 2023). Organizations need to maintain advantage in the big data age, with the capacity to organize big data (BDATLC) being crucial. BDAC enhances business efficiency by increasing revenues, market shares, and returns

(Saputra et al., 2022). BDA end customers have twice the chance of economic success as they make decisions five times faster (Huang and Wang, 2017). Companies with skilled data analysts outperform others in overall return (Dubey et al., 2019). Retailers using BDA saw 15–20 percent increased returns. Organizations can strengthen success through talent management procedures that utilize data effectively. While focusing on improving firm competitiveness, big data analytical talent in strategic marketing enhances market share. Firms must implement efficient talent management to leverage big data advantages (Shamim et al., 2019). Organizations can enhance marketing by using data mining, predictive analysis, and machine learning to extract insights from customer data.

- H2A: TC/ HR Capability has a positive relationship between BDAC and organization performance (OP)

2.6 Innovation Capabilities and Organization Performance

According to Zhang and Hartley (2018), innovation positively affects SMEs' organizational performance through both positive and negative mediating effects, linked to product performance and process innovation. The effect intensifies through factors like innovation orientation, R&D investment, and external partnerships, especially for small companies. Welch et al. (2020) examined how dynamic executive capability of exploration and exploitation affects business performance. Various innovation forms have a positive influence on operational efficiency, with studies showing a positive relationship between marketing innovation and company growth (Hussain et al., 2020; Kafetzopoulos et al., 2020). Innovation enhances company results by enabling organizations to adjust operational processes in response to market changes (Cinar et al., 2020). Chen et al. (2020) found that organizational innovation positively correlates with efficiency in Chinese firms.

- H2B: Innovation capabilities have a positive impact on OP

2.7 Firm Ambidexterity and Organization Performance

Ambidexterity can reinforce a firm's performance and refers to a firm's ability to exploit and explore simultaneously. This is supported by Yanuar and Fontana (2022), who suggest that the capability to exploit and explore simultaneously assists firms in adjusting to market or economic changes and difficulties, which enhances performance. Lastly, the concept of ambidexterity has recently been demonstrated as an important feature to be adaptable and profitable in the long term in the context of a company's performance or efficiency (Li et al., 2020) because firms are simultaneously expanding both exploratory and exploitative processes.

- H2C: Firm Ambidexterity is positively related to superior OP

2.8 Firm Agility and Organization Performance

Agility alleviates risk and enables firms to respond to market changes through diversification, innovation, and product reformulation. Agile firms can capture market share, reduce costs, and increase profitability. Ravichandran and T (2018) confirmed agility's positive impact on firm performance. Organizational agility functions as a dynamic capability that helps firms adapt resources for competitive advantage in shifting markets (Rialti et al., 2019; Dubey et al., 2019). Research suggests companies can use BDA to enhance organizational agility, as confirmed by Ciampi et al. (2022). BDA generates data enabling businesses to detect and respond to market changes (Côrte-Real et al., 2017). Quick reaction to market opportunities enhances competitive advantage and increases market share (Zhou et al. 2019).

- H2D: Firm agility positively impacts OP

2.9 Organisational performance, dynamic TC, and strategic alignment

Whenever BDA operations as well as human capacity operate in accordance with company strategy, organisations function effectively (Mikalef and Gupta, 2021). Strategic cooperation provides advantage to the BDA through making sure that personnel efforts carry forward future company objectives. Fosso Wamba et al. (2024) note that strategic orientation and talent-driven BDA practices synergistically influence firm performance. Misalignment leads to poor data initiative prioritization and lack of management support. Strategic alignment enables dynamic TC and company performance in BDA contexts.

- H3A: The relationship between dynamic TC and OP is significantly affected by strategic alignment.

2.10 Knowledge Flow, Innovation Capabilities, and Organization Performance

Organizations increasingly use BDAC to enable innovation and enhance performance. Knowledge flows both inside and outside organizations determine how BDAC enhances innovation performance. An information network around innovation is vital for organizations to utilize insights from dynamic information flows. Mikalef et al. (2020) note that knowledge resources significantly affect BDAC's promotion of innovation-driven performance. Big data provides organizations with information, but its value emerges only when shared efficiently across functional domains. BDAC integration into organizational strategy is more effective than isolated innovation. Research shows information flow moderates BDAC, innovation, and performance outcomes. Mikalef et al. (2020) found firms with strong information flows better convert analytical capabilities into innovation. Organizations capable of absorbing and transferring knowledge perform better in data-rich environments, suggesting that poor knowledge flow of BDAC-developed innovation can lead to underperformance.

- H3B: Knowledge Flow affects the relation between innovation and OP

2.11 Environmental Turbulence: Market and Technological, Firm Agility and Organization Performance

Ashrafi et al. (2019) state that agility is vital in turbulent environments where businesses face shifting consumer and technological trends. Agility enables businesses to respond to customer demand changes, innovate, expand market share, enter new markets, and increase profitability at lower costs. Agility helps business performance through technological disruption by enabling operational and strategic adaptation. Ghasemaghaei and Calic (2019) demonstrated that technological disruption enhances digital agility's benefits in achieving strategic outcomes. According to Ravichandran (2018), agility enables faster decisions and innovation in dynamic environments, crucial for performance. Mikalef et al. (2020) argue that agile organizations better respond to market signals and customer needs, leading to improved results.

- H3C: Technology uncertainty favourably influences the correlation between the agility and OP
- H3D: The market's volatility improves the association among agility and OP.

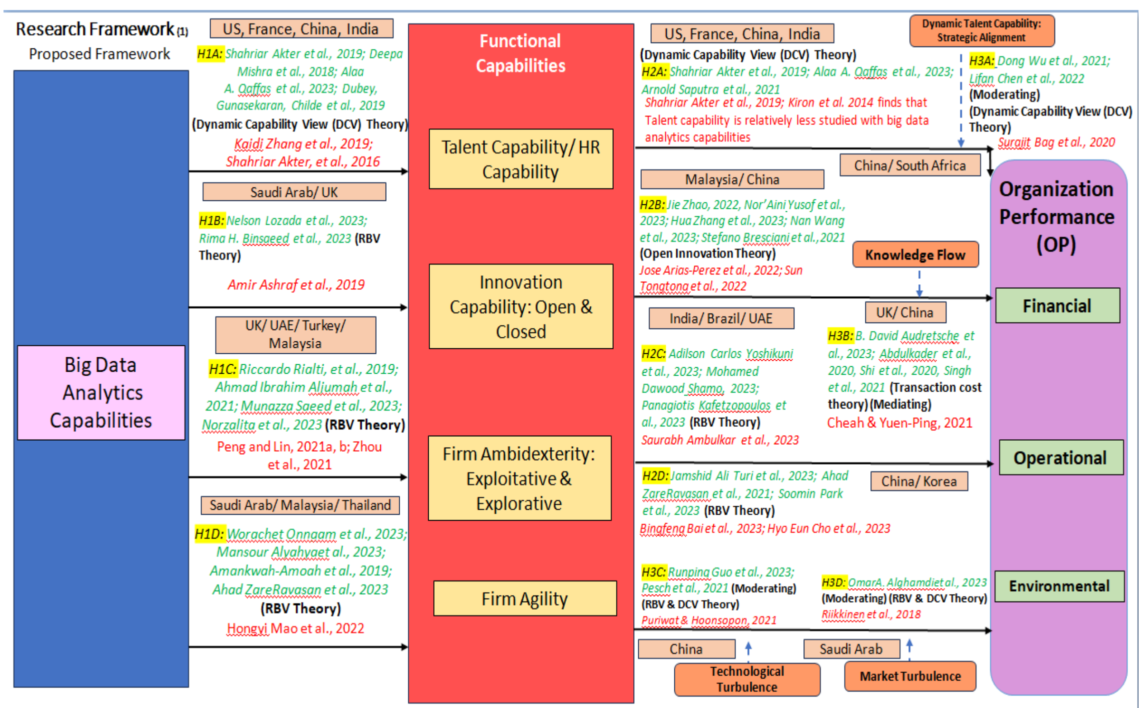

Figure 1: Research Proposed Framework

The empirical study on the connection among BDAC and organisation achievement in information technology companies, particularly in a growing marketplace environment, in addition to functional abilities including personnel and imaginative thinking, has been lacking throughout the existing literature. Nevertheless, nothing has been discovered regarding how flow of information, fluctuations in the environment, along with strategic consistency influence those connections. Furthermore, most previous studies concern large companies and do not pay attention to small and medium enterprises. The suggested conceptual model (Figure 1) fills these gaps by incorporating BDAC, functional capabilities, and contextual factors to explain the performance outcomes of organizations in the Indian IT industry.

3. Methodology and research methods (for research and theoretical papers).

3.1 Sampling Plan

The research was aimed at organizations involved in the IT sector in India that had already implemented BDA, with the respondents being both executives and IT experts who were directly or indirectly involved in administering, making decisions, implementing, and monitoring BDA processes. These respondents were selected because of their current understanding of the technological implementations that are essential for the existence of organizations in a competitive market. A purposive and judgmental sampling technique was used to select 650 professionals in the field of IT services to ensure that there was correspondence with the study objectives. The structured questionnaire was used in the form of data collection and the analysis was carried out with the help of the Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4 using established measurement scales. The unit of measurement as well as structure models, the modifying components (knowledge flow, environmental turbulence, and strategic alignment), as well as the connections among BDAC, functioning capabilities, as well as organisational effectiveness have all been evaluated within the framework of the investigation's methodology. Through representing BDAC as an evolving organisation capacity, the approach established theoretical improvements along with offering IT organisations useful guidance regarding how to integrate analytics-based techniques through their company's success.

3.2 Study description

The implementing BDA IT businesses across India comprised the participant sample. Executives and IT professionals having understanding of relevant advances in technology who participated in BD leadership through execution and evaluation comprised the attendees. The method of purposeful sampling makes the ability for researchers to select individuals who fit the interviewing criteria to accomplish the investigation's objectives. This collection improves from academic and practical applications besides providing deep findings. The technique is both affordable and efficient, allowing the identification of competent individuals (Stratton 2024). By reducing lower on the length of time required to identify qualified individuals, this strategy simplifies management queries. Regarding supplier chain-oriented BDA, research designs have been altered from previous research. Although upper management assessed external reliability, a BDA research validated the information's accuracy. Seven-point Likert ratings were used in the survey, with responses ranging from (1) Strongly disagree to (7) Strongly agree for organisational effectiveness, while (1) Not at all to (7) Extremely significant for the vast majority of questions. PLS-SEM, that is more appropriate for covariance-driven modelling of structural equations instead of complicated structures, has been used during the analysis of data (Ooi et al., 2021). According to Lew et al. (2020), PLS-SEM requires fewer predictions regarding size of sample along with data distribution. This method produces useful inferential data regardless of how fundamentally affects everyday decision-making (Hew et al., 2016).

3.3 Software

Technology called SmartPLS 4 was utilised for analysing the collected information. During study involving multiple concepts, structural equation modelling, or SEM, should be considered given that it provides simultaneously estimation of intricate connections. Partial Least Squares Structural Equation Modelling (PLS-SEM), that would be suitable for exploration studies that involve complex models that have formative and reflective features, was utilised for this research (Hair et al., 2022). In light of its prediction tendency as well as ability for handling irregular data sets, PLS-SEM had been selected.

4. Results.

4.1 Demographics

Of the 650 participants, 49.85% were among between the ages of 18 to 30, 43.08% belonged among the age of 31 and 45, as well as 7.08% belonged among the age group of 46 and 60. Of the people who responded, 73.08% were men as well as 26.92% are women. In regard to company size, 32.15% work for businesses having less than 200 workers, 34.15% for businesses having 201–500 employees, while 33.69% for companies without in excess of 500 employees. By annual turnover, 30.31% were microenterprises (up to 5 crore), 36.15% small enterprises, and 33.54%

medium enterprises (250 crore). For industry experience, 37.69% had 1-5 years, 31.54% had 6-10 years, and 21.85% had over 10 years, while 8.92% had less than one year. Data was filtered by removing non-engaged responses and inconsistencies. The study used previous BDA measurement scales for content validity (Akter et al., 2016). Reliability and validity tests authenticated the measurement model. VIF values below 3 indicated no multicollinearity or common method bias, confirming data validity for PLS-SEM analysis.

Table 1: Demographic Profile of Respondents

Gender	**Frequency**	**Percentage**
Male	475	73.08
Female	175	26.92
Age		
18–30	324	49.85
31–45	280	43.08
46–60	46	7.08
Enterprise scale		
<200	209	32.15
201–500	222	34.15
>500	219	33.69
Industry expertise		
<1 year	58	8.92
1–5 years	245	37.69
6–10 years	205	31.54
>10 years	142	21.85
Annual Turnover		
Micro: 5 Crore	197	30.31
Small: 50 Crore	235	36.15
Medium: 250 Crore	218	33.54

4.2 Measurement model assessment

The outer measurement model was evaluated using composite reliability, convergent validity, and discriminant validity (Schuberth et al., 2018). The model included BDAC, TC, Innovation Capability, Firm Agility, Firm Ambidexterity, Knowledge Flow, Dynamic TC: Strategic Alignment (DTSAC), Environmental Turbulence, and Organizational Performance. Higher-order constructs were assessed using a reflective-reflexive method. Table 2 shows item loadings exceeded 0.70, with Cronbach alpha, rho A, and composite reliability values above 0.70, confirming internal consistency. Average Variance Extracted (AVE) values above 0.50 established convergent validity (Fornell and Larcker, 1981; Hair et al., 2019). The Fornell-Larcker criterion and HTMT ratio verified discriminant validity, with AVE square roots exceeding inter-construct correlations and HTMT values below 0.85 (Henseler et al., 2015). These findings validate the measurement model for testing structural relationships.

Table 2: Quality criterion for model assessment

Construct / Indicator	Items	Loadings/Weights	Cronbach's α	rho_A	CR	AVE
BDAC	BDAC1	0.81	0.87	0.88	0.91	0.62
	BDAC2	0.84				
	BDAC3	0.79				
	BDAC4	0.76				
	BDAC5	0.83				
Talent Capability (TC)	TC1	0.77	0.85	0.86	0.89	0.62
	TC2	0.81				
	TC3	0.84				
	TC4	0.79				
Innovation Capability (IC)	IC1	0.73	0.88	0.89	0.91	0.6
	IC2	0.78				
	IC3	0.81				
	IC4	0.83				
	IC5	0.75				
	IC6	0.8				
Firm Ambidexterity (FA)	FA1	0.76	0.84	0.85	0.88	0.59
	FA2	0.79				
	FA3	0.81				
	FA4	0.74				

Firm Agility (FAg)	FAg1	0.82	0.86	0.87	0.9	0.64
	FAg2	0.84				
	FAg3	0.8				
	FAg4	0.77				
Dynamic TC: Strategic Alignment (DTSAC)	DTSAC1	0.79	0.83	0.84	0.88	0.61
	DTSAC2	0.82				
	DTSAC3	0.76				
Knowledge Flow (KF)	KF1	0.81	0.84	0.85	0.89	0.61
	KF2	0.79				
	KF3	0.82				
Environmental Turbulence (ET)	ET1	0.74	0.82	0.83	0.87	0.58
	ET2	0.78				
	ET3	0.8				
Organizational Performance (OP)	OP1	0.83	0.9	0.91	0.93	0.65
	OP2	0.85				
	OP3	0.8				
	OP4	0.78				
	OP5	0.82				
	OP6	0.84				

	OP7	0.81				

Table 3: Fornell–Larcker Criterion approach for discriminant validity

Construct	BDAC	TC	IC	FA	FAg	DTSAC	KF	ET	OP
BDAC	**0.79**								
TC	0.62	**0.79**							
IC	0.58	0.55	**0.77**						
FA	0.51	0.49	0.52	**0.77**					
FAg	0.56	0.53	0.59	0.54	**0.8**				
DTSAC	0.49	0.51	0.47	0.45	0.52	**0.78**			
KF	0.57	0.54	0.6	0.48	0.55	0.5	**0.78**		
ET	0.42	0.39	0.44	0.41	0.43	0.38	0.4	**0.76**	
OP	0.64	0.6	0.66	0.59	0.63	0.55	0.61	0.47	**0.81**

5. Discussion.

5.1 Summary of findings

Table 4 shows BDAC's combined direct (0.32) and indirect (0.28) effects on organizational efficiency (0.60). BDAC plays a crucial role in IT sector automation and customer adjustment through predictive analytics. Table 5 confirms hypotheses H1A–H1D, proving BDAC significantly increases agility, ambidexterity, talent, and creative thinking. Studies show BDAC promotes technological progress (Su et al., 2022), improves disruption responsiveness (Dubey et al., 2019; Bhatti et al., 2025), and cultivates dynamic abilities. BDAC combines multiple assets to maintain service quality standards in IT businesses. Performance is enhanced by dynamically talent-driven supply chain agility capabilities (DTSAC), with impacts of 0.36 and 0.55 (Table 4). H2A significance shows organizational efficiency is directly affected by TC. Talent forms the expertise core in IT services, with competition based on utilizing skilled workers. Workforce agility and digital expertise are crucial for IT firms in unpredictable markets found AI-powered learning enhances talent productivity. TC facilitates BDAC's effect, converting analytics insights into client solutions and market sensitivity.

Table 4: Direct, Indirect, and Total Effects

Relationship	Direct Effects on OP	Indirect Effects on OP	Total Effects	VAF
BDAC → OP	0.32	0.28	0.6	0.467
TC (TC) → OP	0.21	0.15	0.36	0.417
Innovation Capability (IC) → OP	0.27	0.18	0.45	0.4
Firm Ambidexterity (FA) → OP	0.24	0.19	0.43	0.442

Firm Agility (FAg) → OP	0.28	0.2	0.48	0.417
Dynamic TC (DTSAC) → OP	0.3	0.25	0.55	0.455
Knowledge Flow (KF) → OP	0.26	0.18	0.44	0.409
Environmental Turbulence (ET) → OP	0.18	0.12	0.3	0.4

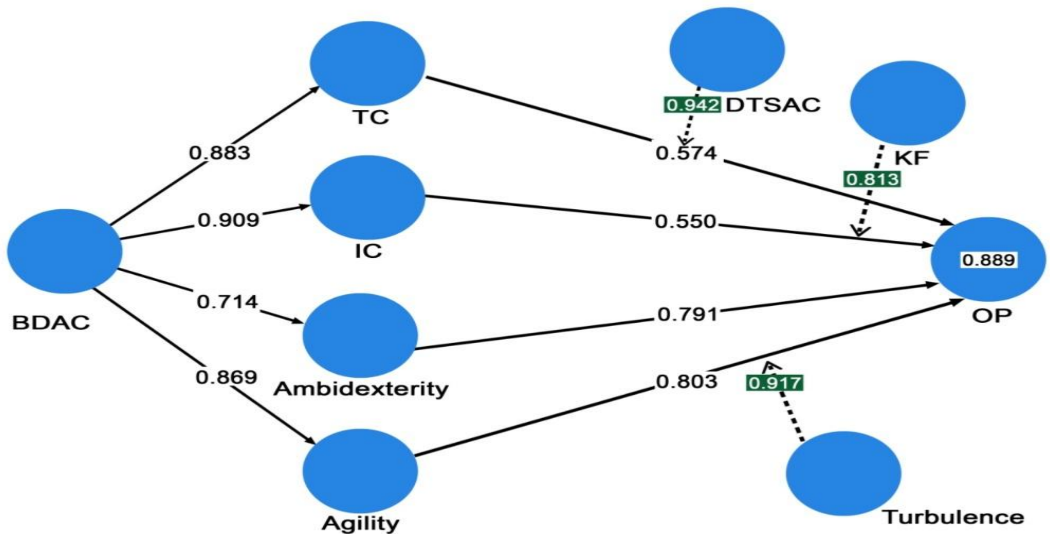

Figure 2: Structural model. Source: Derived from the SmartPLS 4 software

Table 5: Hypothesis Table

Hypothesis	**Relationship**	**t-value**	**p-value**	**Decision**
H1A	BDAC → Talent/HR Capability	8.215	$p < 0.001$	Supported
H1B	BDAC → Innovation Capability	7.842	$p < 0.001$	Supported
H1C	BDAC → Firm Ambidexterity	6.934	$p < 0.001$	Supported
H1D	BDAC → Firm Agility	7.101	$p < 0.001$	Supported
H2A	Talent/HR Capability → OP	5.982	$p < 0.001$	Supported
H2B	Innovation Capability → OP	6.45	$p < 0.001$	Supported
H2C	Firm Ambidexterity → OP	5.732	$p < 0.001$	Supported
H2D	Firm agility → OP	6.103	$p < 0.001$	Supported

H3A	Strategic Alignment moderates TC → OP	4.621	p < 0.001	Supported
H3B	Knowledge Flow moderates Innovation Capability → OP	4.287	p < 0.001	Supported
H3C	Technological turbulence moderates Agility → OP	3.991	p < 0.001	Supported
H3D	Market Turbulence moderates Agility → OP	4.212	p < 0.001	Supported

All p-values are significant at $p < 0.001$ based on bootstrapping results in SmartPLS. The importance of innovation capability (0.45) and ambidexterity (0.43) is evident in the results, supported by H2B and H2C in Table 5. IT companies survive by balancing current IT infrastructure exploitation and disruptive technology implementation. Flexible IT companies optimize service delivery performance and invest in new technologies, enabling innovation while maintaining reliable operations. Firm agility (FAg) impacts IT at 0.48 on average (Table 4), confirmed by H2D in Table 5. In IT services, agility signifies the capacity to adapt techniques, respond to customer demands, and modify business models amid technological innovation. Agile approaches increase IT project success in uncertain environments. These findings align with Teece et al. (2016), who emphasized flexibility as key in unpredictable technological environments. Knowledge flow (KF) significantly impacts achievement (0.44), as shown in Table 5, H3B, demonstrating innovation and performance's moderating impact.

IT personnel globally collaborate through effective information circulation. Liu et al. (2022) demonstrated AI systems enhance collaboration. Data circulation links BDAC, innovation, and talent utilization in IT, driving efficiency. Results show IT providers perform best when BDAC, talent, innovation, ambidexterity, agility, and knowledge flow operate effectively. While technologically facilitated services are valuable and unique resources from an RBV perspective, agility and knowledge flow can complicate procedures. IT companies achieve sustainable performance by coordinating capabilities into a dynamic ecosystem rather than targeting isolated capabilities.

5.2 Managerial Implications

Big Data Analytics Capability (BDAC) influences organizational performance directly and indirectly through talent development, innovation, ambidexterity, and agility. This study provides insights for IT managers on integrating data-driven decision-making into organizational culture rather than just using analytics tools. IT managers should focus on talent upskilling, knowledge sharing, and collaborative learning environments to accelerate innovation and adapt to customer needs and digital technologies. Organizations must remain agile in unstable digital landscapes with cybersecurity issues and disruptive technologies. Strategic alignment maximizes human resource investments by linking analytical skills development to business objectives, while organizational agility helps firms seize opportunities and respond to market changes. IT managers must develop elastic strategies, enhance collaboration, and implement agile frameworks like DevOps to transform capabilities into sustainable competitive advantage.

5.3 Theoretical implications

By extending above the examination of specific correlations among BDAC as well as organizational effectiveness, this investigation extends to the existing body of research. The investigation adopts a configurational strategy that integrates numerous organization abilities—such as talent capability, innovation, ambidexterity, and agility— into an integrated structure, although previous investigations have determined these relationships individually. Through introducing modifying variables includes flow of information, strategy alignment, and environmental turbulence, the investigation additionally offers a contextually contingent strategy that clarifies the conditions at the boundary under which BDAC operates effectively. A greater understanding of the manner in which BDAC translates towards organizational efficiency has been rendered attainable by this multifaceted approach. This research contributes to Partial Least Squares Structural Equation Modelling by examining interaction effects. Through implementation in the Indian IT industry, where innovation agility and digital transformation drive competition, this study validates BDAC's role as a facilitator of dynamic learning and strategic adaptation in digital environments.

6. Conclusions

The efficiency of the IT services industry is investigated in regard to BDAC, TC, innovation, agility, and information flow. Nevertheless, there are some significant limitations. The longitudinal approach makes it challenging to determine how modifications within ability influence effectiveness over the course of time. A longitudinal investigation ought to strengthen this connection since BDAC and innovation fluctuate over time (Su et al., 2022). The research's restricted relevance for additional digital environments, including finance or healthcare IT, comes through its focus on specific IT service providers (Bhatti et al., 2025). It overlooks the impact of external institutional constraints on IT approaches in global delivery of services when evaluating the internal capacities. Future research can expand this work through longitudinal studies exploring BDAC, innovation, and agility development (Dubey et al., 2019; Liu et al., 2022). Studies on IT subfields may reveal varying capacity-performance links. Mixed-method research can illuminate management practices in operationalizing ambidexterity. Post-pandemic IT service viability factors should be examined (Su et al., 2022). Multi-country studies could show how culture and organizational structures affect BDAC-performance relationships (Teece et al., 2016). These recommendations can enhance RBV and TCE understanding while providing practical knowledge for managing multinational digital markets.

Acknowledgment

We appreciated the resources as well as support given to us by Jaipuria Institute of Management, Jaipur Campus, India.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could haveinfluenced the work reported in this paper.

Funding Declaration

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

Ethics Approval and Consent to Participate

The study was conducted in accordance with institutional ethical standards. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. No personally identifiable information was collected.

Data Availability Statement

5.3.1 The data that support the findings of this study are available from the corresponding author upon reasonable request.

AI Use Disclosure

The authors declare that no generative artificial intelligence tools were used in the conceptualization, data collection, analysis, or interpretation of the research findings. Any AI-assisted tools, if used for language editing or formatting, did not influence the intellectual content of the study.

Author Contributions

Prachi Sharma: Conceptualization, Formal Analysis, Writing– Review & Editing.; **Dr. Lokesh Vijayvargy**: Investigation, Software, Visualization; **Dr. Srikant Gupta**: Supervision, Methodology, Validation, Writing, Data Curation, Resources

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