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Research article

Influencing mechanism of the intellectual capability of big data analytics on the operational performance of enterprises

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ABSTRACT

In the era of big data, data processing capability is key to gaining a competitive advantage for businesses. With appropriate technical and organizational resources in place, enterprises can extract considerable value from the vast amount of available data, thereby increasing their competitive advantage. Therefore, to utilize big data resources effectively, enterprises should focus on improving the intellectual abilities of big data analysts. Big data analytics intellectual capability (BDAIC) refers to the specialized skills and knowledge that employees of the enterprise possess, including technical, technical management, business, and relational knowledge, that would enable them to use analytics tools to accomplish organizational tasks and shape the core competitiveness of an enterprise. This study constructs a theoretical model that focuses on the mediating role of person-tool fit and examines the mechanisms by which BDAIC affects an enterprise's operational performance. The results show that BDAIC, which contains four basic categories of knowledge, positively influences an enterprise's operational efficiency. Additionally, person-tool matching mediates BDAIC's effect on an enterprise's operational performance. These findings explore the latest avenues of exploration in the research paradigm of big data analytics. Furthermore, this study has important implications for practitioners trying to use big data to improve business performance.

1. Introduction

In this age of consumer connectivity, businesses generate and receive large amounts of data from the outside world. According to the Internet Data Center (IDC), data exploded from 2010 to 2021, with global data volumes of 33 zettabytes in 2018, and is projected to grow to 175 zettabytes by 2025. This data explosion poses a significant challenge to traditional computer technology; however, the wealth of information behind big data has enabled businesses to grow rapidly. Big Data Analytics (BDA) refers to the use of statistical techniques such as machine learning, factor analysis, and various other statistical tests to analyze big data for decision making [1]. The ability to analyze big data has become a strategic element in business operations [2]. The market value of big data was valued at $70.5 billion in 2020 and is expected to increase to $243.4 billion in 2027, growing at a CAGR of 19.4 % [3]. By 2025, it is expected that approximately 30 % of big data will require advanced real-time big data analytics processing [4].

Superior big data analytics capabilities enable enterprises to use these analytics to analyze data in-depth; proactively identify,

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assimilate, and control strategically valuable organizational resources; and further contribute to the building of resource coordination capabilities that generate business value. A worldwide survey found that 84 % of leading enterprises launched big data analytics schemes to improve the accuracy of their decision making.[1] However, the current global data utilization rate is less than 0.1 %, resulting in a significant waste of data resources. By 2025, 80 % of midsize businesses that utilize modern data processing methods for big data analytics will end up failing [5]. An enterprise's big data analytics capabilities must be acquired through long-term training and practical accumulation. The knowledge of the enterprise's big data analysts and their managers' data management ability will have a significant impact. Therefore, big data analytic ability is considered to be an ability that is closely related to people.

With the surge in the amount of data and the advancement of information technology, an increasing number of scholars are focusing on big data analytics. Some scholars have argued that BDAIC is the specialized knowledge and skills that analytics professionals possess and includes three primary dimensions and 11 sub-dimensions [6]. Existing research sheds light on the significance of BDAIC on the performance of business operations [7,8]. Alkhatib et al. [9] highlighted big data analytics expertise and capabilities as key elements in achieving successful big data-related business value. The lack of data governance and inefficient training of employees in data-handling skills trigger sub-optimal business decisions and higher perceived risk, leading to operational inefficiencies [10]. Therefore, it is particularly important to explore the mechanisms through which big data analytics capabilities can improve enterprises' operational performance. However, the existing research lacks empirical evidence, and few scholars have explored the mechanisms that influence the relationship between BDAIC and enterprise performance.

Operational performance is the ultimate expression of an enterprise's operating results, and is considered a key factor in the overall performance of a business. Researchers are increasingly focusing on analyzing the impact of big data on business operational performance. Mikalef et al. [11] pointed out that BDAIC positively influences the marketing and technological capabilities of enterprises by enhancing their dynamic capabilities, which, in turn, improves their operational performance. Ghasemaghaei and Calic [12] also proposed that BDAIC positively influences enterprises' operational performance (i.e., financial returns, operational excellence, and customer perspectives) through innovation performance. The insights gained from real-time analysis of the massive amounts of data generated by an enterprise's operations can be utilized to help the enterprise make better decisions [13]. Previous studies have analyzed the impact of big data analytics on enterprises' operational efficiency from multiple perspectives. Big data analytic ability is considered to be a people-related ability [14]. However, the existing literature fails to elucidate the mechanism of the effect of BDAIC on enterprises' operational performance, particularly the matching of people and tools that underpin the effectiveness of big data initiatives by staff. Therefore, this study uses person-tool fit as a mediating factor to investigate the role of BDAIC in business operational performance.

Based on previous theoretical studies, this paper focuses on the following research questions.

(1) Can BDAIC improve the operational performance of a business?

and.

(2) What are the mechanisms through which BDAIC affects an enterprise's operational performance?

In order to answer the above questions, this study utilized the analytical approach of structural equation modeling to examine the impacts of BDAIC on an enterprise's operational performance, which contains four basic categories of knowledge (i.e., technical, management, business, and relationship knowledge).

2. Theoretical frame

The resource-based view (RBV) is used to explain how enterprises utilize resources at their disposal to achieve and maintain competitive advantage and is one of the most important and widely used theories in business operations [11]. The RBV suggests that enterprises with unique resources that give them a competitive advantage improve their operational performance. The possession of specific resources by an enterprise is defined as "the stock of available factors owned or controlled by the enterprise" [15]. These resources include two categories: tangible and intangible assets. In this case, tangible assets include capital, equipment, technology, or facilities. By contrast, intangible assets are employee skills. Different resources have different levels of importance to an enterprise, and only resources that are difficult to imitate, rare, and valuable can increase its competitiveness. Many scholars have conducted research on the basis of this theory while modifying it to fully explain why organizations gain competitive advantage and stand out in the face of unpredictable change [16]. In the information system-related literature, scholars have used a resource-based view to explain how organizations use IT resources (e.g., assets and skills) to create business value [10,17,18]. BDAIC is the ability of an enterprise's big data processors to utilize data mining techniques to conduct data mining and interpret big data analysis results. It can be seen that BDAIC is a vital resource for enterprises and is conducive to creating business value, improving operational performance, and building central competitive advantages.

Over the last decade, dynamic capabilities have become an important theory in the field of strategic business management and technology, attracting scholars in both business and IT management [11]. The dynamic capability view, which is based on the RBV,

[1] https://www.statista.com/statistics/742935/worldwidesurvey-corporate-big-data-initiatives-and-success-rate/.

explains how enterprises respond to rapid changes in their organizational environment and customer needs [19]. Dynamic capabilities enable enterprises to reconfigure tangible and intangible assets to adapt quickly to changing conditions, helping them maintain their core competitive advantage over time [20]. In this theory, the term “dynamic” reflects an enterprise’s “ability to update its capabilities to adapt to changing circumstances” [21]. Chen et al. [22] confirmed that the impact of an organization’s use of data analytics can be understood through dynamic capabilities. Dynamic capability theory shifts the focus from the enterprise to the external environment and its responses. More critically, enterprises should adapt their existing operational models to meet changing needs [19]. Dynamic capability is a unique process that integrates, reconfigures, acquires, and releases resources. This is key to improving the ability of enterprises to respond to internal and external challenges and meet changes in market demand. From this, it can be seen that the resources an enterprise possesses are key to determining the capabilities it can develop and the value it can bring. It has been proposed that marketing analytics capabilities are the dynamic capabilities of an organization that can be further strengthened through the adoption of big data analytics. Overall, dynamic capabilities have the potential to eliminate some of the drawbacks of the RBV as a mechanism. Capability as a mechanism has the potential to eliminate some of the drawbacks of RBV, and dynamic capabilities help sense, grasp, and reorganize business processes to ensure effectiveness and competitive advantage [23,24]. Big Data Analytics Capability is a key tool for improving an enterprise’s competitiveness in a highly dynamic marketplace. Thus, enterprises can increase their common and dynamic capabilities by improving their BDAIC [7]. Based on these views, this study constructs a theoretical model to analyze the effects of BDAIC on an enterprise’s operational performance.

3. Theoretical context and hypotheses development

3.1. Big data analytics intellectual capability and operational performance

BDAIC is the professional skills and knowledge of big data mining professionals and includes four dimensions: technical, technical management, business, and relational knowledge [25]. Data experts who take full advantage of big data technology can effectively coordinate business processes and improve the efficiency and quality of decision making [26]. Data analysts are key factors in gaining value, because their talents generate knowledge, skills, information, and competencies [27]. In addition, good business and relational knowledge enable big data mining professionals to better understand an enterprise’s policies and strategies, enhance communication with various business units, and identify and react quickly to changes in the enterprise’s operating environment [28].

Technical knowledge refers to the expertise in big data mining technology acquired by big data mining professionals. Strong technical knowledge is a prerequisite for organizations to implement big data projects and release the value of big data to improve their operational performance. Technical knowledge is a part of big data analysis and is a core competitive advantage for organizations to ultimately achieve results [29]. Therefore, we propose the following hypothesis.

H1. Technical knowledge of BDAIC positively affects an enterprise’s operational performance.

Technical management knowledge enables people to manage big data resources to accomplish organizational tasks using technology resources to extract the intelligence required from big data. For example, Netflix’s big data staff can use visualization and demand analysis tools to understand consumer preferences [30]. Big data analysts are key elements in the interpretation and transformation of data. They use relevant technical methods to mine the key factors affecting business operations from big data and provide decision support to managers. Therefore, having the appropriate technical management knowledge can improve the efficiency of big data analysts, which in turn allows the enterprise’s big data resources to be effectively “developed, mobilized and used” [31]. Therefore, this study proposes the following hypothesis.

H2. Technical management knowledge of BDAIC positively affects operational performance.

A clear understanding of the internal and external environments of an organization by big data personnel is paramount for the successful application of big data. Business knowledge refers to the knowledge owned by big data mining professionals that helps them analyze the internal strategy and external business environment of an enterprise’s operations and make business decisions in the context of big data. Having good business knowledge increases the sensitivity of data professionals to the opportunities and dangers of the external environment and guides business executives in making sound decisions that capture market opportunities and guard against potential dangers [6]. Big data personnel are familiar with information about the enterprise market environment, as well as consumer activities, preferences, and needs, which helps them understand business issues and develop appropriate big data processing solutions [32]. Based on the above analysis, the following hypothesis is proposed.

H3. Business knowledge of BDAIC positively affects operational performance.

Relationship knowledge comes from the perspective of the big data mining department, specifically, its ability to coordinate and communicate with other departments in the enterprise and external partners. It helps big data personnel understand the current needs of other business units, customers, and partners, as well as anticipate their future needs [20]. In addition, a good working relationship between the manager of a big data department and other functional managers is conducive to developing excellent big data analytics skills [33]. The willingness to share new insights and knowledge between different departments within an organization also ensures the success of its big data analytics [14]. Close interaction and smooth collaboration between big data personnel can promote close interaction within the organization and increase the efficiency of information utilization, improving the operational performance of the enterprise [34]. Therefore, we propose the following hypothesis.

H4. Relational knowledge of BDAIC positively affects operational performance.

3.2. Mediating role of person-tool fit

A well-matched big data tool helps improve the efficiency of big data processors, which, in turn, aids enterprises in efficiently conducting data mining and obtaining business-critical information from big data [35,36]. Based on the idea of matching, Ebrahimi et al. [37] argued that big data mining professionals should reach a state of good fit with the tools they use. A high degree of fit between employees' skills and the tools they use allows them to achieve better work outcomes and encourages them to challenge themselves to work at a higher level [38]. This high level of fit enables employees to fully utilize data analytics tools to demonstrate their ability to work and to enhance their understanding of changing markets and customer needs, thereby improving business performance in relation to their abilities. This high degree of people-tool fit enables employees to respond better and faster to changes in the market and customer needs. By contrast, when this adaptation is low, employees who have difficulty performing a task will either avoid it or take longer to perform it, or the rate of error will increase, ultimately leading to poor decisions and having to repeat the task. Accordingly, we propose the following hypothesis.

H5. Person-tool fit mediates the effects of BDAIC on operational performance.

The conceptual model of this study, based on the above hypotheses, is presented in Fig. 1.

4. Research methodology

4.1. Instruments

To ensure the reliability and validity of the measured variables, this study combined a questionnaire design with relatively well-established measures from existing literature. The first part of the questionnaire explained the use of survey results, confidentiality, and other related issues to the respondents. The second part collected basic information about the survey respondents. Ten questions regarding gender, age, education, and industry engagement were posed in this section. The third part was a measurement scale that included six variables: technical knowledge, technical management knowledge, business knowledge, relational knowledge, operational performance, and person-tool fit. Questions related to the measurement of each variable were set in relation to the purpose of this study. Specific measurement questions are shown in Table 1.

4.2. Data collection and sample

The questionnaire was sent to employees responsible for big data processing within the enterprise. Due to the impact of the COVID-19 outbreak, the questionnaire could only be distributed online. A total of 320 questionnaires were returned; we excluded four that were incomplete or had the same answers to all questions, resulting in 316 valid questionnaires, with a valid return rate of 98 %. The statistical results of this survey (see Table 2) show that 20 % of the respondents were male and 80 % were female. In terms of age distribution, the age group with the highest percentage was 20–29 years (48 %), followed by 30–39 years (37 %). Most employees earned between ¥ 3000 and 8000 per month. Bachelor's degree accounted for the largest share of highest academic qualifications at 67 %, followed by master's degree at 21 %. The respondents were evenly distributed in terms of industry. Most enterprises were state-owned and private, and most had fewer than 1000 employees, with a relatively even proportion of years of establishment. The majority of random survey respondents were staff and middle managers in various departments.

5. Data analysis and results

This study adopted SPSS 26.0, and AMOS 24.0 to process the data and obtain the results needed to validate the theoretical model. First, the model fit, validity, and reliability were tested. Second, regression models were constructed for hypothesis testing. Finally,

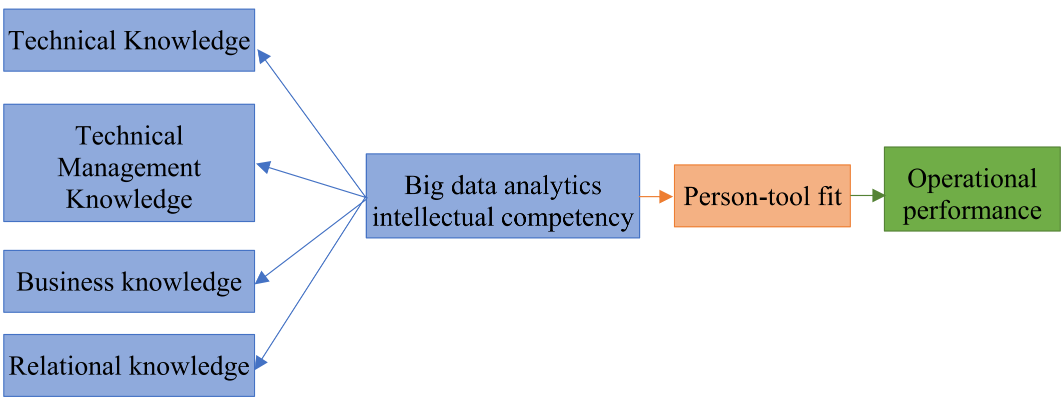

Fig. 1. Research framework and hypotheses.

Table 1
Questionnaire items.

Variable	Items	Source
Technical knowledge	TE1: Our big data mining professionals have high-level programming skills. TE2: Our big data mining professionals are well equipped to manage the project lifecycle. TE3: Our big data mining professionals are well equipped to perform data and network management and maintenance. TE4: Our big data mining professionals create high-performing decision support systems.	Akter et al. (2016)
Technical management knowledge	MA1: Our big data mining professionals are able to accurately grasp technology trends and frontiers MA2: Our big data mining professionals are highly capable of learning new technologies. MA3: Our big data mining professionals are well placed to gain insight into the key factors that make a business run efficiently. MA4: Our big data mining professionals are well aware of the role of big data analytics as a means to an end, not an end in itself.	
Business knowledge	BU1: Our big data mining professionals have knowledge and understanding of company's policies and programs. BU2: Our big data mining professionals have both a high level of ability to interpret business problems and develop appropriate technical solutions based on them. BU3: Our big data mining professionals are familiar with the business functions of an organization. BU4: Our big data mining professionals are able to gain insight into the business environment in which organizations operate.	
Relational knowledge	RE1: Our big data mining professionals are well able to plan, organize and lead projects. RE2: Our big data mining professionals have a high level of teamwork and work well in a collegial environment to plan and execute work. RE3: Our big data mining professionals are well positioned to train other staff members. RE4: Our big data mining professionals are able to work closely with our clients to maintain good customer relationships.	
Operational performance	OP1: Significant improvement in on-time delivery rate over the past three years. OP2: Significant reduction in order fulfilment lead times over the last three years. OP3: Significant improvement in inventory turnover over the last three years. OP4: Significant improvement in capacity utilization over the past three years.	Dubey et al. (2019); Srinivasan and Swink (2018)
Person-tool fit	PT1: There is a good fit between the capabilities of the analytical tools available to us and the tasks my organization is responsible for. PT2: The analytical tools we have available help my organization do its job. PT3: The analytical tools we have available provide good support for implementing the organization's mandate.	Vogel and Feldman (2009)

mediation effects were tested using process macros.

5.1. Assessment of construct measurements

The measurement model was quantified using confirmatory factor analysis to check the reliability and validity of the structure. The measurement model had a good model fit (see Table 3): $x^2/df = 1.934$, TLI = 0.955, CFI = 0.962, IFI = 0.962, NFI = 0.925, and RMSEA = 0.054. As shown in Table 4, the Cronbach's alphas for technical knowledge, technical management knowledge, business knowledge, relational knowledge, operational performance, and person-tool fit were 0.872, 0.860, 0.840, 0.866, 0.882, and 0.850, respectively, all greater than 0.7. This indicated good data reliability across variables and good internal consistency between the questionnaire items. In addition, the composite reliability (CR) of all exceeded 0.80, exceeding the threshold of 0.7 [39]. The factor loading of each observed variable exceeded 0.7, and the average variance extracted (AVE) of the variables were 0.6307, 0.6048, 0.5674, 0.6193, 0.6529, and 0.6534 respectively, with all AVEs greater than 0.5. This indicated good convergent validity for each variable.

5.2. Model testing results

5.2.1. Correlation analysis

Correlation analysis was conducted on six variables: technical knowledge, technical management knowledge, business knowledge, relational knowledge, operational performance, and person-tool fit (Table 5). Technical knowledge ($r = 0.712$, $p < 0.01$), technical management knowledge ($r = 0.732$, $p < 0.01$), business knowledge ($r = 0.740$, $p < 0.01$), and relational knowledge ($r = 0.752$, $p < 0.01$) were significantly and positively related to operational performance. Similarly, technical knowledge ($r = 0.693$, $p < 0.01$), technical management knowledge ($r = 0.711$, $p < 0.01$), business knowledge ($r = 0.747$, $p < 0.01$), and relational knowledge ($r = 0.692$, $p < 0.01$) were positively associated with person-tool fit. Finally, person-tool fit was significantly and positively correlated with operational performance ($r = 0.744$, $p < 0.01$).

5.2.2. Results of hypothesis testing

Data for the six variables of technical knowledge, technical management knowledge, business knowledge, relational knowledge, operations performance, and person-tool fit were standardized and tested using hierarchical multiple regression. The results are shown

Table 2
Demographics of the survey respondents.

Factors	Category	Sample	Percentage
Gender	Male	63	20 %
	Female	253	80 %
Age	Over 50 years old	7	2.2 %
	40–49 years old	24	7.6 %
	30–39 years old	116	36.7 %
	20–29 years old	151	47.8 %
	Less than 20 years old	18	5.7 %
Monthly income	Less than 3000 ¥	80	25 %
	3000–5000 ¥	111	35 %
	5000–8000 ¥	93	29 %
	8000–20,000 ¥	29	9 %
	More than 20,000 ¥	3	1 %
Academic qualifications	PhD	5	2 %
	Master's	65	21 %
	Bachelor's	213	67 %
	Junior College	25	8 %
	Other	8	3 %
Industry	Automotive	4	1 %
	Energy	9	3 %
	Chemical/Biological	13	4 %
	Electronics	13	4 %
	Electrical	7	2 %
	Food	7	2 %
	Steel	3	1 %
	Petrochemicals	4	1 %
	Pharmaceuticals	22	7 %
	IT	21	7 %
	Real Estate	3	1 %
	Catering	6	2 %
	Transportation	4	1 %
	Machinery Manufacturing	7	2 %
	Service Industry	90	28 %
	Other Industries	103	33 %
Type of company	Government-owned Business	102	32 %
	Joint Venture Capital	28	9 %
	Wholly Foreign-Owned Company	19	6 %
	Private Business	89	28 %
	Other	78	25 %
Company size	Less than 100 Persons	105	33 %
	100–500 Persons	98	31 %
	500–1000 Persons	65	21 %
	1000–3000 Persons	22	7 %
	3000–8000 Persons	11	4 %
	Over 8000 Persons	15	5 %
Job type	Senior Management	17	5 %
	Middle Management	62	20 %
	Grassroots Management	58	18 %
	Staff	179	57 %
Department	Human Resources Department	47	15 %
	Product development department	34	11 %
	Marketing department	43	14 %
	Finance department	50	16 %
	IT department	15	5 %
	Other departments	127	40 %
Year of establishment	<1 Year	30	10 %
	1–3 Years	79	25 %
	3–5 Years	63	20 %
	5–10 Years	74	23 %
	>10 Years	70	22 %

Table 3
Model fitting results.

Model Fit Index						
CMIN/DF	RMSEA	NFI	RFI	IFI	TLI	CFI
1.934	0.054	0.925	0.912	0.962	0.955	0.962

Table 4
Construct reliability and convergent validity.

Model Construct	Model Construct	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha	CR	AVE
Technical knowledge (TE)	TE1	0.736	0.832	0.872	0.872	0.631
	TE2	0.708	0.843			
	TE3	0.760	0.822			
	TE4	0.700	0.846			
Technical management knowledge (MA)	MA1	0.703	0.822	0.860	0.859	0.605
	MA2	0.728	0.812			
	MA3	0.712	0.818			
	MA4	0.678	0.832			
Business knowledge (BU)	BU1	0.703	0.784	0.840	0.840	0.567
	BU2	0.665	0.801			
	BU3	0.694	0.788			
	BU4	0.630	0.816			
Relational knowledge (RE)	RE1	0.750	0.815	0.866	0.867	0.619
	RE2	0.724	0.825			
	RE3	0.680	0.843			
	RE4	0.708	0.832			
Operational performance (OP)	OP1	0.702	0.864	0.882	0.883	0.653
	OP2	0.755	0.844			
	OP3	0.740	0.849			
	OP4	0.775	0.835			
Person-tool fit (PT)	PT1	0.730	0.778	0.850	0.850	0.653
	PT2	0.706	0.803			
	PT3	0.720	0.789			

Table 5
Correlation analysis.

	TE	MA	BU	RE	OP	PT
TE	1					
MA	0.820**	1				
BU	0.802**	0.850**	1			
RE	0.763**	0.773**	0.812**	1		
OP	0.712**	0.732**	0.740**	0.752**	1	
PT	0.693**	0.711**	0.747**	0.692**	0.744**	1

Note: **p < 0.01.

in Table 6.

Model 1 tested the effects of technological knowledge on operating performance. The p-value was $p < 0.001$, indicating that the model passed the significance test, and that technological knowledge had a significant effect on operating performance. The coefficient of determination (R^2) was 0.507, and a high degree of raw data was explained by the model. The regression coefficient (β) was 0.712, indicating that technological knowledge positively affects operational performance. Therefore, H1 is supported.

Model 2 tested the effects of technical management knowledge on operating performance. The p-value was $p < 0.001$, indicating that the model passed the significance test, and that technical management knowledge had a significant effect on operating performance. The coefficient of determination (R^2) was 0.574, and the raw data was explained to a high degree by the model. The regression coefficient (β) was 0.450, indicating that technical management knowledge positively affects operating performance. Therefore, H2 is supported.

Table 6
Results of hypothesis testing.

Dependent	Model 1		Model 2		Model 3		Model 4		Model 5	
	OP		OP		OP		OP		OP	
Independent	β	t	β	t	β	t	β	t	β	t
TE	0.712	17.983***	0.343	5.316***	0.234	3.515***	0.15	2.294	0.099	1.605
MA			0.45	6.978***	0.253	3.344***	0.19	2.61	0.141	2.05
BU					0.337	4.664***	0.175	2.333	0.055	0.754
RE							0.348	5.567***	0.294	4.958***
PT									0.33	6.519***
F	323.399		210.603		156.961		136.786		132.533	
R^2	0.507		0.574		0.601		0.638		0.681	

Note: ***p < 0.001.

Model 3 tested the effect of business knowledge on operating performance. The p-value was $p < 0.001$, indicating that the model passed the significance test and that business knowledge had a significant effect on operating performance. The coefficient of determination (R2) was 0.601, and the raw data was explained to a high degree by the model. The regression coefficient (β) was 0.337, indicating that business knowledge positively affects operating performance. Therefore, H3 is supported.

Model 4 tested the effect of relational knowledge on operating performance. The p-value was $p < 0.001$, indicating that the model passed the significance test and that relational knowledge had a significant effect on operating performance. The coefficient of determination (R2) was 0.638, and the raw data was explained to a high degree by the model. The regression coefficient (β) was 0.348, indicating that relational knowledge positively affects operating performance. Therefore, H4 is supported.

5.2.3. *Mediating effect of person-tool fit*

In the research model constructed for this study, BDAIC (i.e., technical, technical management, business, and relationship knowledge) is the independent variable X, operational performance is the dependent variable Y, and person-tool fit is the mediating variable M. Analysis of the mediating effects was performed using the Process macro in SPSS 26.0. Specifically, Model 4 was chosen to test whether person-tool fit mediates the relationship between BDAIC and business operational performance.

The results are shown in Table 7. The positive effect of BDAIC on operational performance was significant ($t = 10.8634$, $p < 0.05$); the effect of BDAIC on operational performance remained significant ($t = 23.4042$, $p < 0.05$) after the mediating variable person-tool fit was added; the positive effect of BDAIC on person-tool fit ($t = 21.2992$, $p < 0.05$) and the positive effect of person-tool fit on operational performance was significant ($t = 6.564$, $p < 0.05$). The mediating effect of person-tool fit is shown in Table 8. The lower and upper bounds of the indirect effects were 0.044 and 0.092, respectively, and did not contain 0. Therefore, the mediating effect was significant, with the mediating and direct effects accounting for 31.76 % and 68.24 % of the total effect, respectively. Therefore, H5 is supported.

6. Discussion and implications

6.1. *Discussion of findings*

To study the impact of BDAIC on enterprises' operational performance, this study constructed a theoretical model, collected data, and verified the research hypotheses.

The following conclusions were drawn.

(1) Technical knowledge positively affects operational performance. With professional technical knowledge, big data personnel will be able to take full advantage of big data analytics technology to maximize its rich value and provide prerequisites for enterprise management to make the right decisions.
(2) Technical management knowledge positively affects operational performance. By managing and deploying big data resources in a planned and rational manner and controlling the execution process of big data projects, the management level of the organization improves, the risk of investing in big data projects is significantly reduced, and thus its operational performance improves.
(3) Business knowledge positively affects operational performance. A high level of business knowledge increases the sensitivity of big data personnel to external opportunities and risks, enabling them to guide relevant business units to make informed decisions, seize opportunities, protect against potential threats, and ensure the correct analysis and management of the enterprise in its current business situation.
(4) Relationship knowledge positively affects operational performance. By building good relationships, it is easier for big data personnel to understand the project's positioning, objectives, and strategy, which helps big data departments communicate better with the rest of the business so that this information can be used and deployed effectively to address new and rapidly changing challenges in an enterprise's operating environment.
(5) Person-tool fit mediates BDAIC and an enterprise's operational performance. Data specialists can rationalize the allocation and processing of an organization's resources during business operations through these capabilities. They can use big data analysis tools wisely to ensure a good fit between the analysis tools and the organization's tasks. This helps the organization better fulfill its tasks, which in turn leads to improved operational performance.

Table 7
Results of mediation model test.

Variables	Operational Performance		Operational Performance		Operational Performance	
	t	p	t	p	t	p
Big data analytics talent capability	10.8634	0	23.4042	0	21.2992	0
Person-tool fit	6.564	0				
R^2	0.6835		0.6397		0.5928	
F	167.9302		184.6392		151.4317	

Table 8
Proportion of mediating, direct, and total effects.

	Effect	BootSE	BootLLCI	BootULCI	Proportion
Mediating effect of person-tool fit	0.067	0.012	0.044	0.092	31.76 %
Direct effect of person-tool fit	0.145	0.016	0.115	0.176	68.24 %
Total	0.212	0.01	0.193	0.231	

6.2. Theoretical implications

First, based on a summary of the literature related to BDAIC, the study classify its connotations into technical knowledge, technical management knowledge, business knowledge, and relational knowledge. Broadened understanding of big data analytics capabilities. Second, the study constructs a theoretical model that concentrates on the mediating role of person-tool fit and examines the mechanisms by which BDAIC affects an enterprise's operational performance, thereby enriching previous research. Finally, this study introduced person-tool fit as a mediating factor. The results show that person-tool fit mediates the influence of BDAIC on an enterprise's operational performance. These findings explore the latest avenues of exploration in the research paradigm of big data analytics.

6.3. Managerial implications

Based on the results of this study, and considering current corporate realities, the following suggestions are made regarding corporate management. First, this study demonstratedsthat big data analysis positively affects an enterprise's operational performance. Therefore, enterprises must focus on the cultivation of big data analysis talent during the practice process. More specifically, enterprises should increase their support for training funds and encourage technical talent to continuously learn about new technologies. With the increase in professional big data processing talent, enterprises can build big data professional teams, improve their efficiency in utilizing big data, obtain richer business information, and improve their competitiveness in the increasingly competitive market. Second, the results show that person-tool matching plays a mediating role in the process by which BDAIC affects an enterprise's operational performance, reminding enterprises not only to train big data analytics talent but also to invest more in data analytics equipment during management practices. This is because a good combination of analysts and analytics tools can better exploit the value embedded in big data, allow the seizing market opportunities, and help business managers make rational decisions quickly, thereby gradually improving business operational performance. Enterprises in the process of running big data analysis should also focus on providing appropriate analysis tools for big data-related personnel to improve the fit between them and the tools they use, and then give full play to the value of big data.

6.4. Limitations and future research

This study constructs a theoretical model to examine the mechanisms by which BDAIC affects an enterprise's operational performance. An online questionnaire was used to collect data, and statistical methods were used to analyze the data and test the research hypotheses. Future research could contend with the effective mining of the impact of BDAIC on enterprises' operational efficiency through technical means and provide more comprehensive management suggestions for market-driven big data operations. Second, this study selected multiple industries for analysis and exploration without delineating them as specific industries; the survey was too broad in scope, and the impact of big data can vary by industry. Future research could be broken down into industries such as high tech, e-commerce, retail, and the Internet to analyze the role of BDAIC in operational performance in different industries. Finally, this study analyzed only the mediating variable of person-tool fit within the enterprise and did not consider whether external variables might have an effect. Future research could consider including other moderating variables to explore the BDAIC from a new perspective.

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Ethics statement

This study did not involve the use of animal subjects or human subjects. All participants provided informed consent to participate in the study.

CRediT authorship contribution statement

Yan Liu: Writing – original draft, Data curation, Conceptualization. **Hong Qiao:** Formal analysis, Data curation. **Junbin Wang:** Methodology, Investigation. **Yunfei Jiang:** Writing – review & editing, Investigation.

Declaration of competing interest

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

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