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Leveraging Big-Data Management for Production Excellence: Decision-Making Capabilities, Decision Quality, and the Moderating Effect of Manufacturing IT Infrastructure

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ABSTRACT

Research aimed to test the influence of big data management on the operational performance of manufacturing companies by improving the company's decision-making quality. The moderating influence of information technology infrastructure was also tested. Survey-based cross-sectional quantitative data collected from 320 manufacturing employees using convenient sampling technique. Study results identified that big data analytical management factor significantly influence to the big data decision-making capabilities. In addition, decision making capabilities also significantly influence to the decision-making quality. In other perspectives, big data decision making capabilities also significantly improve decision making quality. Further moderating effect of information and communication technology also strengthen the effect of big data decision making capabilities on decision making quality. The study with this significant moderating effect extended the contribution in the existing research framework with the moderating effect of information and communication technology in strengthening data-driven decision processes. Study also contributed practically to suggest that companies should have proper investment to improve the company's decision-making process that could strengthen the decision-making capability to improve performance. Study also contributed to help to the manager in focusing on the development of data-driven decision skills to enhance operational performance. Companies can use these insights to build effective data and technology systems that drive better operational performance.

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1. Introduction

In a data-driven business culture, a company's primary focus is on the big data analysis management (BDAM) practices to increase the operational performance (OP) (Panigrahi et al., 2023). During the rapid advancement in technology, big data management potential is supporting the operational functions, which improve the companies' OP (Paramesha et al., 2024). In the industrial and engineering environment, the ability to analyze the large volume of data sources is critical for achieving efficient OP (Panigrahi et al., 2023). Equally, BDAM also empowers companies in optimizing the production process, which improves the company's operational functions (Sahinyazan et al., 2021). Literature supported that when the companies have stronger BDAM then it leads to an improved decision-making process. BDAM helps companies to manage large volumes of data, which strongly improves the big data decision-making capabilities (BDDC) (Jeble et al., 2017). Improving in decision-making could lead to improvement in optimized processes, resource allocation, and overall OP (Provost & Fawcett, 2013). However, to realize these benefits, companies require access to data, which depends entirely on their BDDC, which is being shaped by BDAM (Shawang et al., 2024). Consequently, BDAM is integral for organizations because it enables companies to improve decision-making to increase OP. From the various BDAM practices, leadership's focus on big data is a foundational element in driving data-oriented initiatives within organizations (Shamim et al., 2019). The leader who understands the significance of big data always promotes a vision that always prioritizes improving the decision-making system in the organizations, which leads to improving the company's OP (Li et al., 2022). Other studies have also highlighted that effective leadership ensures that data analytics projects align with organizational goals and receive adequate resources to increase BDDC (Adepoju et al., 2023).

Equally important is talent management for big data, which involves attracting, developing, and retaining professionals with analytical expertise and problem-solving skills. Organizations that effectively manage big data talent can interpret analytical insights more accurately and apply them effectively in operational and strategic decisions (Tabesh et al., 2019) to improve the OP. Another vital determinant of big data capability is technology readiness, which encompasses those tools and the platforms that improve BDDC to increase OP (Arowoogun et al., 2024). Other authors also reflected this argument to explain that without an appropriate technology infrastructure, companies are not able to manage meaningful insights, which is important to improve BDDC (Mikalef et al., 2018), which could hinder the company's OP. On the other hand, organizational culture further influences how effectively big data initiatives are implemented to improve companies to improve company's OP. A culture that encourages innovation, collaboration, and openness to technological change raises BDDC (Gade, 2021), thereby improving companies' OP. All of these factors determine that organizations can transform the raw data into actionable intelligence, which improves the BDDC to increase the company's OP. Further, when the companies have better BDDC, then the companies are better position to increase the decision-making quality (DMQ) (Riipa et al., 2025). High-quality decisions are characterized by accuracy, timelines, which are important for OP (Mikalef et al., 2018). In other perspectives, information technology infrastructure (ITI) is important to improve the BDDC of the organizations that could leads to improve the DMQ (Naqvi et al., 2021).

A strong IT infrastructure ensures that data flows smoothly across different organizational units, analytics tools function optimally, and decision-makers have real-time access to reliable information (Balogun et al., 2021). Such kind of technology supports strengthens the company's efficiency in improving better decision-making system. Enhanced decision-making quality significantly contributes to superior OP through improving productivity, resource utilization, and quality control (Sahoo, 2021). Based on these relationships, current research formulated how the data analytics leadership, talent management, technology, and organization culture improve the company's BDDC and DMQ, which in turn improve the OP. It also evaluates how IT infrastructure moderates between BDDC and DMQ, making data-driven systems more effective. Along with the growing body of literature on BDAM and decision-making, prior literature is still limited in various ways. Firstly, from the variable point of view, previous studies have majorly focused on BDAM and firm performance (Arowoogun et al., 2024; Gopal et al., 2024; Ji-fan Ren et al., 2017; Ram & Desgourdes, 2024; Rashid et al., 2025), while these studies have limited focus on OP that could improve through better decision-making processes of the organizations (Jiang et al., 2024; Makhloufi et al., 2023; Olatunji, 2025; Riipa et al., 2025). Therefore, this study contributed literature were showing that BDAM could improve the BDDC to improve OP. Furthermore, the relationship between DMQ and OP has often been treated as linear and direct, without sufficient attention to the underlying decision-making capabilities that bridge big data usage and performance outcomes (Ajegbile et al., 2024; Ershadi et al., 2025; Hosen et al., 2024; Riipa et al., 2025). Hence, there remains a need for a more holistic model that links organizational, technological, and human factors to data-driven decision-making and its eventual influence on OP.

In this regard, the study contributed literature where BDAM improve the BDDC, which in turn improves the DMQ to enhance companies' OP. Another major gap lies in the limited examination of moderating effects, such as the role of ITI for strengthening the association in BDDC and DMQ. On the other hand, prior researches have acknowledged IT resources to improve BDDC Gupta and George (2016); Pantović et al. (2024), to improve the OP is still inadequate. Furthermore, prior studies had attention on other sectors (Khan, 2022; Müller et al., 2018; Riipa et al., 2025). Limited attention is given to engineering-related or manufacturing sectors, where BDDC can have profound implications for OP (Awan et al., 2021; Gade, 2021). Furthermore, studies examining how BDDC translate into improved performance remain scarce (Ghasemaghaei et al., 2018; Tian et al., 2022). Thus, this study addresses these gaps through developing a comprehensive model that investigates the joint influence of leadership, talent, technology, and culture on BDDC, and how these capabilities improve DMQ and OP while considering the moderating role of IT infrastructure in the context of developing industrial economies. The study with the above objective contributes to both theory and practical aspects. From a theoretical view, the current study extended how big data-related resources drive superior decision-making and OP. While, from the practical perspective study also provides some valuable insights to develop an environment through leadership commitment, skilled talent management, technological readiness, and supportive culture in achieving long-term operational performance (Biswas et al., 2024). The next chapter was a literature review where both of theoretical and practical aspects were discussed. Research methodology highlighted the research design and sampling techniques. Study results highlighted the main findings and their interpretation. Lastly, a discussion of study findings, which is supported by the prior studies, has been highlighted.

2. Literature Review

2.1 Theoretical Framework

Study framework comes under the shadow of two theories, namely the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT), where both of the theories provide a comprehensive lens to enhance decision-making quality (DMQ) and operational performance (OP). According to the RBV theory, Barney and Arikan (2005) highlighted that firms gain performance through their unique resources. In the current study framework, variables like big data capabilities, which are resources of the companies are effectively help individuals to increase the company's OP through increasing the company's operational decision-making process (Shamim et al., 2019; Shan & Wang, 2024). Other studies also enforced that big data capabilities increase the BDDC to gain OP (Wang et al., 2023). Although RBV underscores the possession of strategic resources, the DCT significantly extended this view through the improvement of internal and external stakeholders to improve OP adopting market changes (Teece et al., 1997). Within this framework, BDDC represents a dynamic capability that helps to the organizations in transforming complex data, increasing OP. Analyzing data ability, and make strategic decisions reflects an adaptive learning process that continuously enhances the firm's operational agility and performance. Furthermore, information technology infrastructure (ITI) acts as an enabling mechanism that enhances these dynamic capabilities by improving data integration, accessibility, and analytical precision, thereby strengthening the link between BDDC and DMQ (Biswas et al., 2024). By integrating RBV and DCT, study theoretical model explains both the possession and application of big data resources for superior OP. The study variables are predicted in Figure .1.

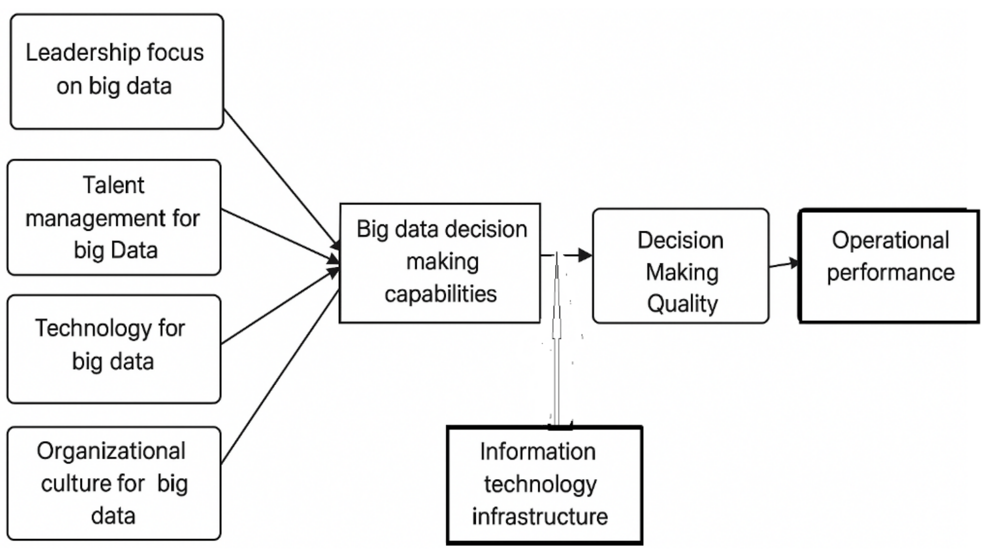

Figure 1: Research Framework

2.2 Hypothesis Development

Leadership focused on big data consisted of the degree where the organizational leaders emphasize on big data in enhancing the analytical processes and informed decision-making (Nisar et al., 2021). The leadership commitment is important for determining big data initiatives that are being effectively implemented and sustained the organization. This is further supported with the view that leaders, along with the clear data driven vision are able to allocate better resources which increases the values analytics-based reasoning (Rahman, 2025). Further study also highlighted that leadership on data basis always significantly promotes the development of analytical competencies and BDDC in the firms (Nisar et al., 2021). Shafique et al. (2024) research also empirically found that leadership played an integral role in integrating big analytics to improve BDDC. Grimaldi et al. (2025) study also further found that data-oriented leaders encourage knowledge sharing, collaboration, and innovation which are significantly increase the BDDC process of the organizations. In the same vein, Riipa et al. (2025) study further noted that leaders with better big data analytics significantly increase the company's decision making process and accordingly hypothesis is, H1: Leadership focus on big data significantly influence to big data decision making capabilities.

In addition, talent management consisted of attracting, and retaining a valuable skilled professional which are being capable of the managing tools in the firms to improves companies better decisions (Hariri et al., 2024). In other sense, better talent management always ensured that better talent not only operate the complex analytical systems but it also increase the better decisions making in the companies (Ojika et al., 2024). Firms who are strategically invest in data talent improve their analytical capacity, problem-solving speed, and the precision of their decisions, creating a competitive edge. Lozada et al. (2023) empirically found that human expertise increases the BDDC meaning that even advanced technology is ineffective without the right talent to interpret and apply insights. Similarly, Niu et al. (2021) revealed that BDDC is largely dependent on how organizations manage and empower their analytical teams. Moreover, Niu et al. (2021) study found the significant relation of talent management with BDDC. These studies enforced that talent management increases the BDDC and accordingly hypothesis is,

H2: Talent management for big data significantly influence to big data decision making capabilities.

In addition to previous, technology in big data consisted of advanced tools that enable companies to in the collection and process large data sets to improve companies decisions (Kumar et al., 2024). Such kind of technologies also help the firms in converting raw data into real-time insights, which significantly leads to more reliable decision-making (Nisar et al., 2021). After the availability of better technologies companies are able to increase the companies analytical performance through providing better decision makers along with accurate information (Oluoha et al., 2022). Furthermore, the latest technologies platform in big data also helps to raise a better coordination and a unified decision-making approach across the organization (Nisar et al., 2021). Sutarman et al. (2025) empirically also found that technology infrastructure significantly affects the firm’s ability to increase companies BDDC. Similarly, Srinivas et al. (2024) study also contended that technology-driven analytical tools enhance the accuracy and timeliness of decisions. Santoso and Surya (2024) also highlighted that advanced technologies reduce data processing time and improve decision precision. These studies shown that technology helps to improve the BDCC and accordingly hypothesis is,

H3: Technology for big data significantly influence to big data decision making capabilities.

Organization culture for the big data consisted of a culture which promotes in the organizations a better decision making processes through proper learning and innovations (Aseeri & Kang, 2023). A culture which helps to provide culture in using the analytical tools in raising employees’ willingness to base decisions on factual information rather than assumptions. When in the companies culture a data-driven mindset is derived then the effective BDDC becomes more structured, consistent, and evidence-based (Riipa et al., 2025). Chatterjee et al. (2024) also argued that companies with the better data driven culture are able to adopt a BDDC. They also found that data culture has significant influence on the BDDC. Rožman et al. (2023) also demonstrated that a supportive culture enhances employee engagement with data and promotes experimentation with analytical tools. Furthermore, Elugbaju et al. (2024) noted that organizations fostering data-based discussions and accountability achieve superior decision-making outcomes. Thus, cultivating a big data–oriented culture is essential for transforming technical resources into sustainable decision-making capabilities that drive innovation and performance.

H4: Organization culture for big data significantly influence to big data decision making capabilities.

Further, BDDC in the companies increases the capacity to interpret vast amounts of data for improved decision outcomes Niu et al. (2021). Other authors highlighted that these capabilities encourage the organization to predict future trends, which significantly enhance decision accuracy and quality. High DMQ reflects decisions that are timely, relevant, evidence-based, and aligned with strategic objectives (Clark et al., 2024). Companies with strong BDDC can anticipate various opportunities, which leads to more consistent and effective decisions. Chen et al. (2024) empirically found that BBDC improves decision accuracy and reduces uncertainty in dynamic environments. Wu et al. (2024) research also found that firms with better BDDC have a greater experience in superior decision reliability, which increases the DMQ. Prakash (2024) also observed that data analytics-driven decisions are more precise and transparent, leading to the best DMQ that increases the OP. Another study also found that BDCC significantly increases the DMQ and accordingly hypothesis is,

H5: Big data decision-making capabilities significantly influence to decision making quality.

In the prior literature, the correlation between BDDC and DMQ has been explored, but this relationship is not clear, which highlights that further study could be conducted in another way. Previous studies highlighted that information technology infrastructure, which consisted of digital communication resources that support in data storage and analysis which increases the stakeholders' decision making capability (Gulzar et al., 2024) though improving accessibility, integration, and responsiveness in information processing. A strong IT infrastructure ensures that data which is flowing seamlessly in the departments is being allowed to the decision maker’s to improve their actions on their real time insights (Muhajji et al., 2024). Such kind of integration also reduces the decision latency which supports to the rapid analytical interpretation which increases overall decision quality (Ajegbile et al., 2024). Rangineni et al. (2023) empirical study also found that IT infrastructure strengthens the link between analytical capability and decision performance through facilitating faster and more reliable data utilization. In the same vein, Isibor et al. (2025) study also demonstrated that a well-developed IT backbone increases data analytics influence on decision accuracy and strategic agility. Adepoju et al. (Adepoju et al., 2022) study also observed that companies with advanced IT infrastructure experience better decision systems because of improved data visibility and analytical synchronization. These prior studies highlighted that IT infrastructure increases the effect of BDDC through creating consistent technological environment that supports timely and effective decisions and accordingly hypothesis is,

H6: Big data decision making capabilities are significantly influence to decision making quality with moderating effect of information technology infrastructure.

OP in the company represents the efficiency and effectiveness of the internal and external processes of the company i.e, production, cost control, and service delivery (Al Majali, 2023). High DMQ ensures that strategic choices are well-informed, which directly influences the company's operational success. Quality decisions help organizations minimize wastage, optimize production planning, and improve coordination across supply chains, leading to enhanced overall performance (Gulzar et al., 2024). Empirical studies consistently reveal a strong relation in DMQ and OP. Medeiros and Maçada (2022) demonstrated that data-based decisions significantly improve organizational agility and productivity. Similarly, Alonge et al. (2023) found that accurate and timely decisions derived from analytics lead to better cost efficiency and customer satisfaction. Furthermore, Jaboob et al. (2024) study also highlighted that HQD help organizations to adapt market fluctuations with more effectively to increase OP. Researchers highlighted that DMQ is important factor to improve the OP and accordingly study hypothesis is,

H7: Decision making quality significantly effects to operational performance.

3. Research Methodology

For the study hypothesis testing, researchers employed the quantitative deductive approach. It enables objective testing of hypotheses through measurable data, ensuring reliability, validity, and generalizability of results (Schutt, 2019). Furthermore, the researcher employed the cross-sectional research approach for the data collection, where data using a self-administered questionnaire. This allows researchers to analyze variables on a single point in short time (Wang & Cheng, 2020). On the other hand, research by nature is explanatory which is providing a deeper understanding of underlying mechanisms (Lalor et al., 2013). In this regard, researchers employed the explanatory nature study.

3.1 Population and Sampling Techniques

Population of the study comprises the manufacturing company’s employees because these employees are directly in the company operations which is making them suitable respondents for examining the study’s variables. A convenient sampling technique used because it is practically ease to access for the participants especially in organizational settings where time and resource constraints often limit the feasibility of random sampling (Etikan et al., 2016). A total of 450 questionnaires were floated among employees, representing the actual sample size. Out of these, 350 questionnaires were returned, indicating a high level of participation and interest in the study. After data screening, 320 questionnaires were deemed valid for final analysis, resulting in an effective response rate that reflects both data reliability and respondent engagement. This response rate is considered satisfactory in social science research, ensuring sufficient representation and validity of the collected data for statistical analysis (Saleh & Bista, 2017).

3.2 Questionnaires Development

Study instrument was adapted from previously published literature, where it had already been validated and tested for reliability. ITI is measured from four dimensions, namely hardware, software, communication and network and database. Each of the dimensions was measured by 3 items and these items were adapted from (Jabbouri et al., 2016). OP comprised from 6 items which were adapted from (Khan et al., 2022). BDDC comprises from 5 items which were adopted from (Shamim et al., 2019). Furthermore, BDAM was comprises from four dimensions namely leadership comprises from 6 items, talent management comprises from 4 items, technology comprises from 5 items and organizational culture comprises from 5 items and every dimension was comprises from prior literature of (Shamim et al., 2019). Lastly, DMQ comprises from 4 items of (Shamim et al., 2019). Every instrument was measured on five-point Likert Scale.

4. Data Analysis and Results

4.1 Demographic Analysis

Study demographic results highlighting that manufacturing companies represent a well-balanced and knowledgeable workforce with diverse backgrounds and experience levels. Most of the respondents were male (66.9%) and while females are (33.1%). Most participants were young to middle-aged professionals, particularly between 25–44 years (66.9%), suggesting that respondents are in their most productive and decision-oriented career stages. Educationally, the dominance of bachelor's and master's degree holders (78.1%) demonstrates that the surveyed employees possess sufficient academic and technical expertise to understand and utilize big data technologies effectively. Furthermore, there are 24.4% respondents are belong to engineering departments further strengthens the study's relevance to technology-driven decision-making and operational improvement. On the other hand, from experience perspectives there are (33.1%) respondents which has 6-10 years' experience, which indicates a mature understanding of their firm's data-driven culture and operational strategies. These demographic results shown that responses reflect informed perspectives from individuals capable of assessing the company operational performance. Table.1 predicted values shown the predicted values.

Table 1: Demographic Profile

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	214	66.9
	Female	106	33.1
Age	Below 25	38	11.9
	25 – 34	116	36.3
	35 – 44	98	30.6
	45 and above	68	21.3
Education Level	Diploma	40	12.5
	Bachelor's	152	47.5
	Master's	98	30.6
	PhD	30	9.4
Department	Production	102	31.9
	Engineering	78	24.4
	Quality Assurance	54	16.9
	Maintenance	48	15.0
	Administration / HR	38	11.8
Experience (Years)	Less than 3	54	16.9
	3 – 5	78	24.4
	6 – 10	106	33.1
	More than 10	82	25.6
Job Position	Operator / Technician	92	28.8
	Engineer / Specialist	114	35.6
	Supervisor / Manager	78	24.4
	Senior Manager / Executive	36	11.2

4.2 Measurement Model

Hypothesis results analyzed through employing Structural Equation Modeling (SEM) through the AMOS software.

4.3 Factor Loadings

The factor loadings in Table.2 results highlighted the degree where each item is being correlated with the underlying construct that is showing the indicator reliability and construct validity. The recommended threshold value for factor loadings in 0.50 which shown that over 50% of the variance in the observed variable is explained by the latent factor. Conversely, loadings between 0.60 and 0.70 can also be accepted in exploratory studies if other validity measures are satisfactory (Fornell & Larcker, 1981). Constructs factors loadings are greater than 0.70 which shown that construct has reliability and construct validity. This recommends that indicators used were both valid and reliable representations of the theoretical constructs under investigation.

Table 2(a): Loadings

Construct	Item	Loading
LEAD	LEAD1	0.871
	LEAD2	0.852
	LEAD3	0.823
	LEAD4	0.884
	LEAD5	0.815

Table 2(b): Loadings

Construct	Item	Loading
TAL	TAL1	0.846
	TAL2	0.863
	TAL3	0.795
	TAL4	0.834
	TAL5	0.773
TECH	TECH1	0.904
	TECH2	0.883
	TECH3	0.855
	TECH4	0.873
	TECH5	0.824
CULT	CULT1	0.802
	CULT2	0.783
	CULT3	0.824
	CULT4	0.763
	CULT5	0.742
BDDC	BDDC1	0.926
	BDDC2	0.897
	BDDC3	0.868
	BDDC4	0.848
	BDDC5	0.799
DMQ	DMQ1	0.909
	DMQ2	0.887
	DMQ3	0.855
	DMQ4	0.814
	DMQ5	0.804
OP	OP1	0.873
	OP2	0.833
	OP3	0.856
	OP4	0.817
	OP5	0.789
DAT	DAT1	0.860
	DAT2	0.848
	DAT3	0.816
HAR	HAR1	0.782
	HAR2	0.893
	HAR3	0.783
SOFT	SOFT1	0.622
	SOFT2	0.742
	SOFT3	0.763
CON	CON1	0.832
	CON2	0.793
	CON3	0.842

Note: LEAD = “Leadership Focus on Big Data”; TAL = “Talent Management for Big Data”; TECH = “Technology for Big Data”; CULT = “Organizational Culture for Big Data”; BDDC = Big Data Decision-Making Capabilities; DMQ = Decision-Making Quality; OP = Operational Performance; DAT-Data Science, HAR-Hardware, SOFT-Software, CON-Communication and Network.

4.4 Convergent Validity

Construct validity could be assessed employing “Cronbach’s alpha, composite reliability (CR), and average variance extracted (AVE)”. Hair et al. (2019) recommend that both Cronbach’s alpha and composite reliability (CR) should be above 0.70 to reflect adequate internal consistency. Likewise, an AVE value higher than 0.50 shows that the construct explains the majority of variance in its measurement items, rather than the variance being attributed to error. In the current study, all construct values are greater than above above-recommended values. The results confirm that the items measuring each construct are contributed significantly contribute to the underlying latent variable (Fornell & Larcker, 1981; Hair et al., 2019). Results are in Table.3.

Table 3: Convergent Validity

Construct	Cronbach's α	Composite Reliability (CR)	AVE
LEAD	0.901	0.921	0.681
TAL	0.882	0.912	0.642
TECH	0.933	0.953	0.753
CULT	0.842	0.884	0.594
BDDC	0.941	0.953	0.782
DMQ	0.932	0.942	0.733
OP	0.903	0.923	0.664
DAT	0.882	0.902	0.623
HAR	0.832	0.913	0.732
SOFT	0.783	0.832	0.673
CON	O.893	0.854	0.632

4.5 Discriminant Validity

Discriminant validity of construct was being through the Fornell and Larcker criteria which suggested that AVE square should always be higher from the diagonal values (Fornell & Larcker, 1981; Hair et al., 2019). The analysis confirmed that all constructs satisfied this condition, indicating that each construct is conceptually and empirically different from others. This demonstrated that construct fulfill the requirement of discriminant validity which is ensuring that all constructs measure unique theoretical dimensions within the proposed framework. Discriminant validity results is in Table.4.

Table 4: Fornell and Larcker

Construct	LEAD	TAL	TECH	CULT	BDDC	DMQ	OP	DAT	HAR	SOFT	CON
LEAD	0.825										
TAL	0.581	0.800									
TECH	0.622	0.562	0.866								
CULT	0.503	0.473	0.492	0.768							
BDDC	0.624	0.674	0.703	0.582	0.883						
DMQ	0.452	0.494	0.524	0.443	0.752	0.854					
OP	0.403	0.433	0.464	0.384	0.682	0.681	0.812				
DAT	0.524	0.504	0.553	0.465	0.553	0.502	0.463	0.787			
HAR	0.353	0.383	0.353	0.321	0.232	0.322	0.232	0.232	0.842		
SOFT	0.234	0.526	0.234	0.232	0.342	0.234	0.123	0.311	0.242	0.883	
CON	0.422	0.343	0.234	0.342	0.123	0.123	0.532	0.233	0.421	0.432	0.821

4.6 Hypothesis Results

After construct reliability and validity testing, next step is hypothesis testing (Table 5) and (Figure 2). The results shown that LEAD shows a significant positive ($\beta = 0.181$, $p < .001$) influence on BDDC which is suggesting that when manufacturing leaders prioritize data-driven strategies and establish a vision for data utilization, employees are more motivated to integrate analytics into operational decisions. Similarly, TAL data also positively significantly ($\beta = 0.252$, $p < .001$) enhances firms' BDDC. Furthermore, TECH demonstrates positive significant ($\beta = 0.303$, $p < .001$) impact on BDDC. CULT also exerts a significant positive effect on BDD. Further results shown that BDD also significantly ($\beta = 0.623$, $p < .001$) enhance DMQ which is highlighting that data-oriented insights allow managers to make more accurate, evidence-based, and timely decisions. Furthermore, ITI also significantly and positively moderates this relationship ($\beta = 0.142$, $p = 0.010$) between BDDC and DMQ, which suggests that when robust IT systems are in place, the effectiveness of big data capabilities on decision quality becomes stronger. Lastly, DMQ also significantly positively ($\beta = 0.551$, $p < .001$) influences OP, which confirms that high-quality, data-supported decisions translate into better production outcomes, reduced errors, improved supply chain coordination, and overall productivity gains in manufacturing firms.

Table 5: Results Hypothesis

Path	β (std.)	SE	t-Value	Decision
LEAD → BDDC	0.181	0.045	4.00	Supported
TAL → BDDC	0.252	0.050	5.00	Supported
TECH → BDDC	0.303	0.047	6.38	Supported
CULT → BDDC	0.122	0.052	2.31	Supported
BDDC → DMQ	0.323	0.055	5.87	Supported
(BDDC × ITI) → DMQ	0.142	0.054	2.59	Supported
DMQ → OP	0.351	0.070	5.01	Supported

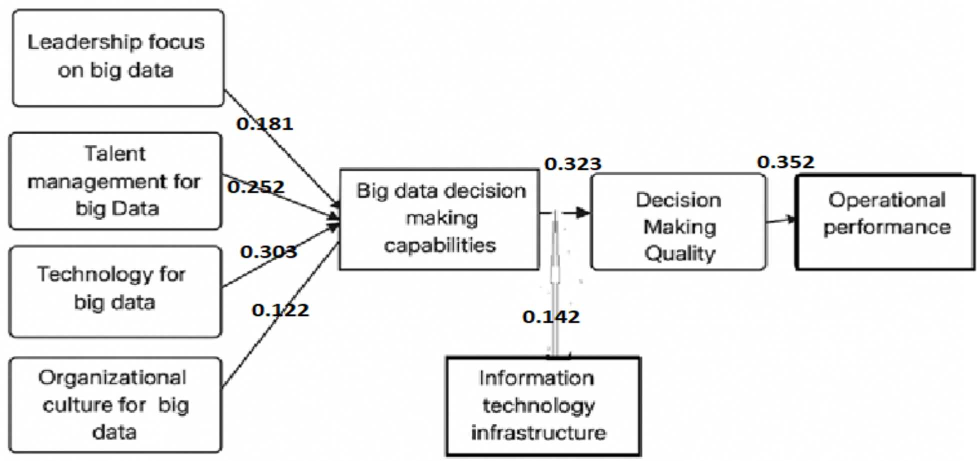

Figure 2: Beta Values

5. Discussion

The study results empirically found the evidence that all relationship between the big data related organizational enablers and BDDC are positive and significant. From the individual relationship perspectives, LEAD in integral in increasing the BDDC among the manufacturing firms. This finding is indicating that in the manufacturing firms top management demonstrated a clear vision for the data driven transformation which is increasing the BDDC. This result is supported with Binsaeed et al. (2023), who argued that leadership vision is fundamental in developing BDDC because it determines organizational readiness and cultural alignment. In the same vein, Gade (2021) study also emphasized that LEAD transforms decision processes through integrating analytics into business models. These findings are more relevant for the manufacturing companies because in the manufacturing environments where operational precision and resource optimization are crucial, LEAD ensures the instutionalization of analytical decision-making. In this regards, strong leadership not only builds a technical competencies competence but it also raises a mindset that embraces data as a basis for strategic decisions.

TAL also has a significant positive influence on the BDDC. These results show that when companies invest in the development of human skills along with analytical and technical expertise improving their BDDC. Kassim (2022) found that TAL enhance analytical capabilities and improve the quality of organizational BDDC. In the same vein, Hariri et al. (2024) findings also noted that TAL contributes directly to organizational learning and performance enhancement. Study findings are more relevant for the manufacturing companies which are being strategically manage their talent to improve their big data insights to optimize production efficiency, predictive maintenance, and supply chain agility. These findings underline that human skills are the operational link between technological resources and effective decision. In this regards, skilled workforce development becomes a necessary complement for the leadership vision which is ensuring that data-driven initiatives are implemented effectively and that insights are transformed into concrete actions in manufacturing processes which could improve company's competitive advantage. The study results further highlighted that TECH also increases the BDDC. This result highlighted that latest technologies in the organizations are central to enabling BDDC in manufacturing. Wong and Ngai (2025) found the same results where found that the technological dimension significantly contributes to firms' ability to make evidence-based decisions. As modern manufacturing operations are totally dependent on predictive maintenance systems, and integrated supply chain analytics and for all these companies requires a stronger technological infrastructure. Companies with presence of these appropriate technologies allow managers to visualize vast amounts of production and operational data which improves the BDDC. In this regard, the manufacturing firms should be focused on the advanced technological systems which could translate big data into real-time operational insights, improving precision, reducing waste, and enhancing operational efficiency.

CULT also has positive and significant influence on BDDC which emphasizes cultural factors role in shaping data-driven behaviors. Literature suggested that in the manufacturing companies if the companies have stronger leadership, talent, and technology in place, the absence of a supportive culture could minimizes full realization of big data benefits. Therefore, the findings shown that along with talent, leadership, and technology, supportive culture is also important for the organization because a supportive culture promotes openness to innovation, collaboration between departments, and trust in data analytics empowers employees to adopt data-based reasoning in their decision-making. Such a culture reduces resistance to change and builds shared values around experimentation and continuous improvement which are being essential traits for manufacturing firms facing dynamic market conditions. Almeida et al. (2025) study found the same results where they highlighted that a data-oriented culture strengthens an organization's capability to utilize analytics effectively by encouraging knowledge sharing and evidence-based practices. These findings emphasized that a big data friendly culture is indispensable for the institutionalization of BDDC. This finding suggests that in manufacturing contexts, where efficiency and precision are critical, organizations must promote a mindset that treats data as a key resource for innovation and operational excellence. In other findings, it is found that BDDC increase the positive effect on DMQ which is suggesting that organizations equipped with analytical and data-driven competencies make more accurate and informed decisions. Almeida et al. (2025), who emphasized that BDDC improve decision precision and organizational intelligence. Further, indirect moderating effect results highlighted that ITI significantly increases the effect of BDDC on DMQ with the moderating effect. This result shown that organization which are stronger in the analytical capabilities are able to make a better quality decisions which are being supported from strong ITI that facilitate data accessibility, integration, and processing. The result are supported with Siddiqui et al. (2024) and Bamel and Bamel (2021), IT infrastructure serves as an enabler that bridges analytical where they found that potential with operational application, ensuring that big data insights translate into superior managerial decisions. On the other hand, DMQ also significantly increase the OP when it is significantly effect from other factors which is confirming that accurate, data-driven decisions directly improve manufacturing efficiency, product quality, and cost management. Mariani et al. (2021) and Celestin et al. (2024) studies also established that big data enhanced BDDC which increases productivity and competitiveness. Thee above findings highlighting that companies with the stronger big data analytical management effectively contribute to BDDC to improve the OP in the manufacturing companies.

6. Contributions and Future Directions

Study has contributions from both of theoretical and practical ways. From the theoretical way, firstly research framework contributed to know how the big data analysis capabilities enhance the decision making process of the manufacturing companies that leads to improve OP. The study with the extended model big data management to improves the decision making process of organizations supported both of RBA and DCT theories which is suggesting that big data analytics management represents in companies unique resources which helps to transform data into better decision making process to improve OP. Secondly, significant moderating effect of information and communication technology between BDDC and DMQ also extended the prior literature through highlighting that technologies not only merely provide to the operational supports but are strategic resources that enhance analytical agility and decision precision. Thirdly, moderating role of ITI also contributed through providing a novel insights through showing that the strength of analytical capabilities depends on the underlying IT environment. This aligns with the socio-technical systems perspective to improve the DMQ to lead OP, which provides empirical support for decision theory and performance management. With the specific findings, study results highlighted that multiple perspectives through extending the RBV and DCT theories, which provide an appreciation of how big data ecosystems function in manufacturing organizations. Lastly, a study research framework could also help the researchers to conduct their research with the extended model to increase the scope of this research framework. From the practical view, study offers different guidance to the manufacturing managers to know the importance of big data analysis management in effectively increasing the decision-making process. Secondly, study results also highlighted the need that companies should have proper investment on training and development of talent management build workforce competence. Thirdly, moderating effect stronger effect also contributed that companies should have continuously up gradation of their data infrastructures to ensure seamless data collection and interpretation. Technology adoption should be aligned with business strategy, enabling efficient and timely decisions that improve production efficiency and quality control. Moreover, the role of organizational culture indicates that management must foster a collaborative and data-trusting environment. Encouraging experimentation, cross-functional communication, and openness to data insights can accelerate the cultural shift toward evidence-based management. With above significant contributions, study has limitation that needs to be addressed in further research. Firstly, study not tested the hypothesis of mediating role of BDDC that limited the predictive relevance of the model. In this regards, further research could be conducted with mediating effect to increase model predictive power. Secondly, study covers the quantitative part of the study while ignored qualitative approach, in this regard further research might be conducted on interviews or observation based to increase research scope. On the other hand, study focused on cross sectional research design where overlooks the benefits of longitudinal design that captures data across multiple intervals. Consequently, future studies may adopt a longitudinal approach to observe potential variations in the findings over time. Lastly, the study was limited to the transportation and engineering manufacturing, while ignoring other retail or SMEs. Therefore, future research could be conducted on retail or SMEs for generalizability increasing.

7. Conclusion

Research aimed to test the influence of big data management on the operational performance of manufacturing companies by improving the company's decision-making quality. The moderating influence of information technology infrastructure was also tested. Survey-based cross-sectional quantitative data collected from 320 manufacturing employees using convenient sampling technique. Study results identified that big data analytical management factor significantly influence to the big data decision making capabilities. In addition, decision making capabilities also significantly influence to the decision-making quality. In other perspectives, big data decision making capabilities also significantly improve decision making quality. Further moderating effect of information and communication technology also strengthen the effect of big data decision making capabilities on decision making quality. The study with this significant moderating effect extended the contribution in the existing research framework with the moderating effect of information and communication technology in strengthening data-driven decision processes. Study also contributed practically to suggest that companies should have proper investment to improve the company's decision-making process that could strengthen the decision-making capability to improve performance. Study also contributed to help to the manager in focusing on the development of data-driven decision skills to enhance operational performance. Companies can use these insights to build effective data and technology systems that drive better operational performance.

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