The Relationship Between Big Data Analytics Capabilities and Business Value in the Construction Industry

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ABSTRACT

The rapid growth of digital data within the contemporary business environment has positioned big data analytics as a strategic resource for enhancing competitive advantage and business performance. While sectors such as manufacturing, supply chain, banking and finance, as well as healthcare have demonstrated established approaches to realising business value from big data, the construction industry remains at an early stage of adoption. Within this context, big data analytics capabilities (BDAC) play an essential role in translating digital data into business value (BDBV). This study aims to examine the relationship between BDAC and BDBV within construction organisations that increasingly generate digital data through their business operations. BDAC is conceptualised as comprising eight dimensions: data, technology, basic resources, analytical skills, managerial skills, data-driven culture, organisational learning, and business alignment. Meanwhile, BDBV is represented by strategic, transformational, informational, transactional, infrastructural, managerial, operational, and organisational values. A questionnaire survey was conducted, and data were collected from 109 construction organisations, including contractors, consultants, and developers operating in Peninsular Malaysia. The research hypothesis was tested using non-parametric statistical analysis in SPSS. The findings indicate that BDAC is positively associated with BDBV, with stronger relationships observed for operational and organisational value dimensions. However, weaker associations were found for transactional and informational values. Overall, the results provide valuable insights for researchers and practitioners seeking to understand better how analytics-related capabilities support business value realisation in the construction industry.

Keywords: Big data analytics, capabilities, business value, construction industry, dynamic capabilities theory

INTRODUCTION

As organisations increasingly operate in environments characterised by vast volumes of digital data, big data has emerged as a strategic organisational resource that supports competitive advantage and improvements in business performance. Recent studies have increasingly examined how organisations can realise business value from big data (Mikalef, Krogstie, et al., 2020; Namasivayam et al., 2025; Park et al., 2020), with big data analytics capabilities (BDAC) identified as a critical enabling factor (Song et al., 2025; Zan et al., 2024). BDAC refers to an organization's capability to acquire, analyze, and effectively use data resources by transforming unstructured data into actionable insights (Ciampi et al., 2021; Mastan et al., 2026). This capability emphasizes how organizations exploit data-driven opportunities rather than merely possessing large datasets. By transforming data from multiple sources into meaningful insights, BDAC plays an important role in shaping effective business models and enhancing organisational performance (Mayndarto, 2025; Novicka, 2025). Consequently, growing scholarly interest has focused on how BDAC contributes to business value and explains the relationship between analytics capabilities and organisational value creation (Namasivayam et al., 2025; Park et al., 2020; Song et al., 2025). Consequently, scholarly attention has increasingly shifted toward investigating how BDAC contributes to business value, with the aim of clarifying the relationship between BDAC and business value.

The construction industry is no exception to this shift. The increasingly complex, project-based, and multi-stakeholder nature of the construction business has placed construction organizations in an increasingly data-driven business environment (Kannan & Abd Rahim, 2025; Li et al., 2023). The increased use of technologies such as building information modelling (BIM), digital project management systems, sensors, and cloud-based platforms has generated vast amounts of digital data, demanding the ability of organizations to manage and leverage that data strategically (Almas, 2025). However, performance in the construction industry has traditionally been assessed primarily through cost reduction, a narrow focus that limits the ability of organisations to recognise and capture broader value from digital technology adoption (Ibrahim et al., 2024; Pekuri et al., 2014). This cost-centric perspective has constrained the effective use of digital data and slowed progress towards more advanced data-driven practices (Adib Hashim et al., 2025; Samuelson & Stehn, 2023). As organisations across various industries, such as manufacturing and healthcare, increasingly recognise big data as a key driver of business success (Friesenbichler & Reinstaller, 2021; Samad et al., 2022; Wang & Zhang, 2024), construction organisations are likewise seeking to advance their digital business strategies by leveraging big data to support value-based outcomes and improve overall business performance (Maaz et al., 2025; Wu & AbouRizk, 2023).

Although big data analytics is widely recognised for its potential to enhance organisational performance, the creation of business value cannot be achieved solely from a business perspective. Instead, organisations can generate business value from big data only when they possess an adequate level of BDAC (Mikalef, Krogstie, et al., 2020; Oesterreich et al., 2022; Wetering et al., 2019). In the construction industry, however, the role of BDAC in translating analytics investments into business value remains underexplored, with existing studies offering predominantly general and fragmented insights (Atuahene et al., 2018; Chaurasia & Verma, 2020; Ngo et al., 2020). Moreover, prior literature reviews within the broader information systems domain have demonstrated that multiple dimensions must be considered when evaluating the business potential of information technology investments (Elia et al., 2022; Klee et al., 2021; Samsuden et al., 2024). The specific characteristics of each technological development must also be accounted for to fully capture the interdependencies through which business value is created at the organisational level (Bisswang et al., 2025; Mikalef, Pappas, et al., 2020; Saleem et al., 2020). Consequently, research on business value in the context of big data analytics has predominantly adopted the notion of BDAC to represent organisations' ability to mobilise and leverage organisational resources for value creation (Elia et al., 2022; Mikalef, Krogstie, et al., 2020). Against this backdrop, it is essential to examine the domain-specific aspects of big data analytics from the perspectives of business and strategic management. Therefore, as scholarly attention has increasingly shifted toward investigating how BDAC contributes to business value, this study seeks to clarify the relationship between BDAC and business value in construction organizations.

LITERATURE REVIEW & HYPOTHESIS

Big Data Analytics Capabilities (BDAC)

Big data analytics is increasingly important for addressing unique organizational requirements essential to developing and sustaining a competitive advantage. BDAC describes an organization's ability to acquire, analyze and effectively use the data as resources to transform unstructured data into valuable insights that can be leveraged for generating economic advantages (Mikalef et al., 2019; Song et al., 2025; Su et al., 2022). Meanwhile, from a strategic management perspective, the BDAC is a significant dimension to generate competitive advantage (Awan et al., 2021; Monino, 2021; Zan et al., 2024). It enables organisations to integrate technological, human, and managerial capabilities to leverage data and unlock business value through advanced analytical techniques (Dang et al., 2025; Elia et al., 2022). This capability highlights organisations' ability to exploit data-driven opportunities rather than merely possessing large volumes of data. By transforming data from multiple sources into meaningful insights, BDAC plays a crucial role in enhancing organisational effectiveness and overall business performance (Mayndarto, 2025; Novicka, 2025).

Building on this understanding, research on BDAC frequently draws on strategic management theory, specifically dynamic capabilities theory (DCT), to provide a theoretical foundation in translating BDAC into business value. DCT introduced by Teece et al. (1997) indicates that organisational success in rapidly changing environments depends on the ability to sense opportunities and threats, seize opportunities through appropriate strategic decisions, and transform existing resources and capabilities to sustain competitive advantage (Anning-Dorson et al., 2025; Samsudin & Ismail, 2019). DCT is viewed as a process of learning and developing new skills to improve organizational performance. Prior research indicated that BDAC is underpinned by three resource categories: tangible resources such as data and technological infrastructure; human skills, including managerial and technical expertise; and intangible resources like a data-driven culture, organizational learning and business strategy alignment (Bag et al., 2021; Dang et al., 2025; Edu, 2022; Mikalef et al., 2019). Collectively, by boosting all of these dimensions, organizations may optimize BDAC, thereby driving innovation and improving their business performance (Mikalef et al., 2019; Orero-Blat et al., 2025; Yasmin et al., 2020; Zan et al., 2024). Organisations that strengthen these capabilities are better positioned to adapt to environmental changes, remain competitive, and convert data-driven initiatives into tangible business value in an increasingly data-intensive business environment.

Big Data Business Value (BDBV)

From a strategic management perspective, big data analytics have been proven to enhance organizational decision-making processes and business operations across domains such as supply chain management, healthcare, and the manufacturing industry, to generate richer insights and improve organizational performance (Cetindamar et al., 2022; Chong et al., 2024; Samad et al., 2022). In the context of this study, BDBV refers to the tangible and intangible benefits that organizations derive from the effective use of big data analytics (Elia et al., 2022; Mikalef, Pappas, et al., 2020; Olszak & Zurada, 2019). Rather than being limited to financial outcomes, business value encompasses a broader range of advantages, including improved operational efficiency, enhanced decision-making, strategic competitiveness, and organizational transformation (Oesterreich et al., 2022; Saleem et al., 2020). From the perspective of the information systems domain, business value is a central consideration when evaluating the business potential of information technology investments (Gellweiler & Krishnamurthi, 2022; Mikalef, Pappas, et al., 2020; Olszak & Zurada, 2019).

The value of knowledge generated in the information systems domain extends beyond what can be captured in traditional financial and accounting reports. The investments of IT business value are widely recognised for generating value in multiple forms rather than through a single measurable outcome. IT business value can be realised in the forms of profitability, organisational performance enhancement, productivity, and business processes efficiency (Gellweiler & Krishnamurthi, 2022; Saleem et al., 2020; Sumbal et al., 2019). At the organisational level, IT business value influences an organisation's performance across different layers of work by contributing to both efficiency improvements and competitive advantage (Hanafizadeh & Tavakoli, 2025; Melville et al., 2004). However, assessing the return on IT business value remains challenging, as the benefits are inherently multidimensional and often require complex multivariate analytical approaches for accurate measurement (Devaraj & Kohli, 2003). To address this challenge, Gregor et al. (2006) proposed a comprehensive classification of IT investment values, encompassing strategic benefits related to customer relationship development, managerial benefits associated with performance monitoring and control, operational benefits linked to cost efficiency and quality improvement, and functional benefits that support communication and collaboration across organizational units.

Consequently, in the context of big data analytics, many researchers propose the concept of business value realized in the information systems domain. In particular, Park et al. (2020) examined business value within big data analytics by focusing on transactional, strategic, informational, and transformational values. Scholars have consistently highlighted that business value from BDA manifests in multiple dimensions, such as strategic, operational, informational, transformational, and organizational outcomes (Abijith & Wamba, 2012; Elia et al., 2020; Saleem et al., 2020; Song et al., 2025; Vitari & Raguseo, 2019). Building on these established conceptualisations, this study adopts the business value framework proposed in prior research and posits that big data analytics is systematically associated with the creation of these distinct business value dimensions.

The Impact of BDAC on BDBV

Big data analytics has been extensively studied and continually developed, underscoring the growing importance of analytics capabilities within organisations. BDAC reflects an organisation's ability to align analytics resources with business strategy in order to support competitive positioning and value creation (Mikalef et al., 2020; Ibrahim et al., 2025). Prior studies indicate that big data analytics capability enables organisations to transform data into meaningful insights that support decision making, innovation, and improved strategic and operational outcomes, thereby contributing to the creation of multiple dimensions of business value (Gao & Sarwar, 2022; Hartmann et al., 2016; Hirschlein & Dremel, 2021; Klee et al., 2021). Accordingly, big data analytics capability plays a central role in enabling organisations to realise significant business value from big data by effectively mobilising and leveraging their organisational resources. Consistent with this perspective, research on business value within the big data analytics domain has predominantly adopted big data analytics capability as a key explanatory construct for understanding how organisations generate business value from data-driven initiatives (Gao & Sarwar, 2022; Park et al., 2020; Vitari & Raguseo, 2019; Ylijoki & Porras, 2019).
Based on the reviewed literature, this study synthesises the dimensions of BDAC and BDBV into a structured mapping. The detailed classification and relationships between these dimensions are presented in Table 1. This table indicates that Elia et al. (2022) and Park et al. (2020) demonstrated that all BDAC dimensions contribute to the formation of the BDBV dimensions with respect to strategic value, suggesting that the combined interaction of multiple capability elements plays a significant role in shaping this contextual outcome. This indicates that a single dominant factor does not determine strategic value, but rather emerges from the cumulative effect of several interrelated dimensions (Grover et al., 2018; Park et al., 2020; Pathak et al., 2021). Similar patterns are also supported by several other authors, who reported that most of the BDAC dimensions influence the formation of other BDBV dimensions such as transformational, informational, and transactional value (Abijith & Wamba, 2012; Moseneke & Brown, 2022; Vitari & Raguseo, 2019). This consistency across multiple contexts implies that specific dimensional interactions are broadly applicable rather than being confined to a specific setting.

Table 1: Mapping analysis between the dimensions of BDAC and BDBV

BDAC Dimension / **BDBV Dimension**	Data	Technology	Basic resources	Analytical skill	Managerial skill	Data-driven culture	Organizational learning	Business alignment
Strategic	a,b,c,e,h	a,b,c,e,h,i	a,b,c,e,h	a,b,e	a,b,e	a,b,e,i	a,b,e,i	a,i
Transformational	a,d,h	a,d,f,h	a,d,f,h	a,d	a,d,f	a,d,f	a,d	a,d,f
Informational	a,d,h	a,d,h	a,d,h	a,d	a,d	a,d	a,d	a,d
Transactional	a,h	a,h,i	a,h	a	a	a,i	a,i	a,i
Infrastructural				g				
Managerial				g				
Operational				g				
Organizational		f	f	g	f	f		f

Source: a=(Park et al., 2020); b=(Elia et al., 2022); c=(Grover et al., 2018); d=(Abijith & Wamba, 2012); e=(Pathak et al., 2021); f=(Moseneke & Brown, 2022); g=(Wang & Hajli, 2019); h=(Vitari & Raguseo, 2019); i=(Song et al., 2025)

Despite the dominance of strategic, transformational, informational, and transactional value in explaining most IT business value of big data analytics, Y. Wang & Hajli (2019) shifted the focus to analytical skills capability as a unifying mechanism shaping the other dimension of BDBV. They argued that analytical skills capability plays a central coordinating role in translating organizational resources, particularly technical skills, into improved efficiency in healthcare service delivery. In contrast, Moseneke & Brown (2022) provided a more selective explanation by focusing on the relationship between several BDAC dimensions, including tangible, human, and intangible resources in shaping organizational value. Their findings highlight that value-oriented considerations act as a key mechanism through which analytics capabilities strengthen organizational culture and align business strategy. Based on these arguments, this study proposes that:

H1: Big data analytic capabilities (BDAC) have a significant relationship with big data business value (BDBV)

METHODOLOGY

Following established approaches in prior studies, this research adopted a questionnaire survey method to collect primary data from construction organisations in Malaysia. The questionnaire-based survey method offers clear advantages for exploratory research and theory testing, particularly in emerging research areas such as big data analytics, where large-scale empirical evidence remains limited (Ciampi et al., 2021). In addition, survey-based methods enable the collection of data from a wide range of respondents, thereby enhancing the reliability and generalisability of empirical findings (Song et al., 2025). Based on these considerations, a questionnaire survey was deemed an appropriate data collection approach for this study. The focus on Malaysia is further justified by national-level initiatives introduced by the Construction Industry Development Board (CIDB), including the Construction 4.0 Strategic Plan, which aims to accelerate digitalisation and encourage construction organisations to explore the business value derived from digital data and analytics.

Data were collected via online and in-person distribution of questionnaires between January 2025 and June 2025. The survey targeted construction organisations that utilise or have implemented digital data through the adoption of digital software in their business and operational activities. Respondents were drawn from four main categories of construction stakeholders, namely contractors, consultants, developers, and clients or project owners. Questionnaires were primarily distributed to managerial-level personnel who were familiar with their organisation's digital data practices and strategic decision-making processes. A total of 380 questionnaires were distributed, of which 109 were valid, yielding a response rate of 28.7%. The responses were analyzed using IBM's Statistical Package for the Social Sciences (SPSS) Version 26 for descriptive (mean, standard deviation, reliability and validity test) and inferential purposes (correlation).

The survey collected respondents' demographic information, including professional background, work experience, organisational type, and level of exposure to big data analytics. Most respondents held middle-management positions (45%), followed by operational-level staff (35%) and top management (20%). Regarding work experience, 58% of respondents reported fewer than 20 years of experience in construction-related fields, whereas 42% reported more than 20 years. Contractors constituted the largest group of respondents (47%), followed by consultants (23%), developers (16%), and clients or project owners (15%). With respect to exposure to big data analytics, 57% of respondents reported no exposure, 21% reported basic exposure, 20% reported moderate exposure, and only 2% reported extensive exposure.

Based on an extensive literature review, supplemented by deductive content analysis, the survey instrument was systematically developed. The questionnaire comprised three sections: demographic, significant dimensions of BDAC, and significant dimensions of BDBV. A five-point Likert scale was used to categorize the responses, with 1 denoting "highly insignificant" and 5 indicating "strongly significant".

ANALYSIS AND RESULTS

Reliability and Validity Assessment

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Internal consistency reliability refers to the extent to which all the items measure the same construct when multiple-item measures of a construct are employed. Internal consistency reliability was assessed using Cronbach's alpha, one of the widely used measures of reliability (Park et al., 2020). The values of Cronbach's alpha for most of the constructs in this study were 0.927. According to Neuman (2022) a Cronbach's alpha above 0.90 indicates excellent internal consistency, suggesting that the instrument used in this study is highly reliable and that the items are consistent in measuring the intended constructs. Construct validity was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity. Previous studies have suggested that KMO values above 0.60 indicate good sampling adequacy (Hair et al., 2010). However, in exploratory studies with a limited number of items per construct and organizational-level data, lower KMO values (cut-off loading to 0.40) may still be acceptable (Daud et al., 2023; Field, 2018). In this study, KMO values ranged from 0.40 to 0.56, indicating marginal but acceptable sampling adequacy, as presented in Table 2.

Table 2: Reliability and validity test results

Construct		**Cronbach's Alpha**	**Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy.**
BDAC	Data	0.927	0.457
	Technology		0.508
	Basic Resources		0.487
	Analytical Skills		0.509
	Managerial Skills		0.449
	Data Driven Culture		0.503
	Organizational Learning		0.459
	Business Strategy Alignment		0.402
BDBV	Strategic value		0.528
	Transformational value		0.406
	Informational value		0.507
	Transactional value		0.524
	Infrastructural value		0.471
	Managerial value		0.407
	Operational value		0.522
	Organizational value		0.556

Hypothesis Testing

The Spearman's rho correlation test is a non-parametric statistical technique used to determine the relationship between variables when the assumption of normality is violated. This method is appropriate for ordinal data and for relationships that do not necessarily follow a linear pattern. Prior studies suggest that non-parametric correlation analysis is more suitable when data deviate from a normal distribution (Field, 2018; Ali & Al-Hameed, 2022). Accordingly, because the data in this study were non-normally distributed, Spearman's rho was used to assess the strength and direction of the relationship between the study variables. In this study, the correlation coefficients were used to assess the relationship between BDAC and BDBV, as presented in Figure 1.

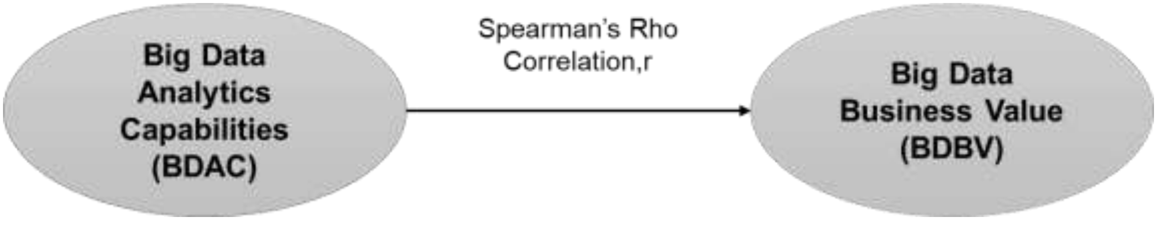

Figure 1: Correlation between BDAC and BDBV

The correlation coefficient ranges from −1 to +1, indicating both the direction and the strength of the association between variables. A positive coefficient reflects a direct relationship, whereas a negative coefficient indicates an inverse relationship. The magnitude of the coefficient represents the strength of the relationship, with values closer to ±1 indicating stronger associations. The interpretation of Spearman's rho is therefore comparable to that of the Pearson correlation coefficient, although it does not require the assumption of normality. Table 3 presents the interpretation of the strength of correlation based on the correlation coefficient value, as suggested by Ali & Al-Hameed (2022).

Table 3: Interpretation of correlation strength according to coefficient values

Value of correlation coefficient, r	**Strength of correlation**
+1	Completely positive correlation
0.70 to 0.99	Strong positive correlation
0.50 – 0.69	Average positive correlation
0.01 – 0.49	Weak positive correlation
0	No relationship

The Spearman correlation results indicate that most of the variables exhibited statistically significant positive associations. Table 4 depicts the correlation matrix between the constructs. Most of the examined variables are positively and significantly associated. Based on the correlation strength classification, the results range from weak to strong positive relationships, indicating consistent associations across contexts. Several BDBV's dimensions, including operational, transformational, and organizational value, demonstrate moderate to strong correlations across multiple variables, suggesting more stable relational structures. The strongest associations are observed in operational value (r = 0.691) and organizational value (r = 0.673), both of which fall within the strong positive correlation category. Conversely, weaker correlations are identified in transactional and infrastructural value, indicating relatively limited associative strength. One non-significant relationship is also observed, suggesting that not all variables are consistently related across contexts. Overall, while these findings confirm meaningful associations, they should be interpreted with caution, as correlation analysis does not establish causality.

Table 4: Correlation between constructs

	Data	Technology	Resource	Analytical Skill	Managerial Skill	Data-Driven Culture	Organizational Learning	Business Alignment
Strategic	.265**	.204*	.261**	.400**	.402**	.418**	.463**	.436**
Transformational	.414**	.432**	.537**	.555**	.510**	.509**	.578**	.544**
Informational	.426**	.344**	.280**	.515**	.432**	.405**	.357**	.344**
Transactional	.166	.314**	.482**	.391**	.161	.452**	.394*	.377**
Infrastructural	.325**	.232*	.144	.382**	.525**	.279*	.249**	.321**
Managerial	.446**	.419**	.519**	.655**	.321**	.650**	.606**	.595**
Operational	.656**	.413**	.382**	.691**	.326**	.507**	.639**	.579**
Organizational	.540**	.347**	.303**	.673**	.423**	.563**	.647**	.471**

Note: **correlation is significant at the 0.01 level; *correlation is significant at the 0.05 level

The hypothesis was tested using Spearman's rho correlation analysis to examine the relationship between big data analytics capabilities (BDAC) and big data business value (BDBV). As presented in Table 5, the correlation analysis reveals a strong positive association between BDAC and BDBV (r = 0.741, $p < 0.05$). A p-value below 0.05 indicates that the relationship is statistically significant. Therefore, the proposed hypothesis is supported.

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Table 5: Hypothesis testing

Spearman Rho Correlation			
		Big data business value	**Result**
Big data analytics capabilities (BDAC)	Correlation coefficient	.741**	
	Sig.(2-tailed) (p-value)	.000	Supported
	N	109	

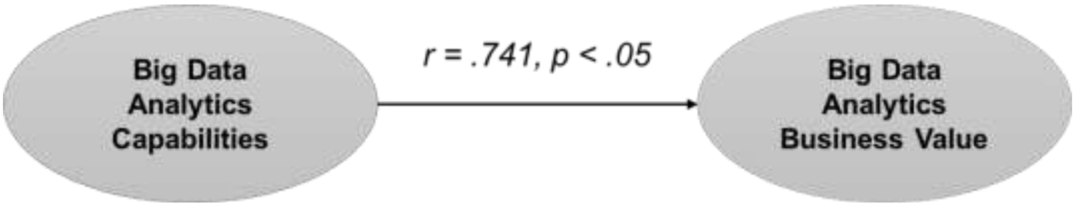

Figure 2: Overall correlation between BDAC and BDBV

DISCUSSIONS

Based on the strength of correlation, the relationships between big data analytics capabilities and business value dimensions range from weak to strong positive associations. This variation indicates that the contribution of analytics-related capabilities to business value creation is not uniform across construction organisations. While specific capabilities, particularly analytical skills, data-driven culture, and organisational capability, demonstrate stronger associations with business value creation, other capabilities exhibit weaker relationships. This pattern reflects uneven levels of big data analytics maturity within the construction industry, where the development and utilisation of analytics capabilities remain inconsistent across organisations. The weaker relationships observed between data and technology capabilities and business value suggest that construction organisations may not yet be fully prepared in these foundational areas, resulting in slower adoption of big data analytics. Although construction organisations increasingly generate large volumes of digital data through technologies such as BIM, project management systems, and site monitoring tools, the ability to integrate and strategically exploit this construction digital data remains limited. Prior studies have highlighted that data in construction are often collected for operational or compliance purposes rather than for advanced analytical use, which constrains the translation of data availability into tangible business value (Whyte & Hartmann, 2017; Sepasgozar et al., 2020).

The coexistence of both weak and strong positive relationships further suggests that big data analytics capabilities do not contribute uniformly to business value across the construction industry. This finding can be explained by the project-based and fragmented nature of construction organisations, in which data practices and the use of analytics often vary across projects and organisational units. Such fragmentation limits the consistent development of analytics capabilities and hinders the systematic realisation of business value from data-driven initiatives (Olanrewaju et al., 2021; Musa et al., 2023). In addition, the mixed strength of the observed correlations may be attributed to the developing-country context of the Malaysian construction industry, where the adoption of advanced data analytics remains at an early stage. Existing studies indicate that construction organisations in developing economies tend to prioritise basic digitalisation and data collection initiatives, whereas the use of advanced analytics for strategic decision-making and value creation remains limited (CIDB, 2021; Sepasgozar et al., 2020). This contextual condition provides a plausible explanation for the weaker associations observed for specific capability dimensions in this study.

Overall, the findings suggest that construction organisations with higher levels of big data analytics capabilities tend to realise greater business value from their digital data. In other words, stronger BDAC are associated with greater business value realisation in the construction industry. Nevertheless, this relationship should be interpreted as a statistical association rather than a causal effect, given the study's non-experimental, cross-sectional design.

CONCLUSION AND IMPLICATIONS

This study provides empirical insights into the relationship between big data analytics capabilities and business value in the construction industry. The findings indicate that analytics capabilities are positively associated with business value dimensions, although the strength of these associations varies across capability areas. This suggests that the development of analytics capabilities within construction organisations remains uneven. From a theoretical perspective, the study contributes to the understanding of data-driven value creation by highlighting the role of organisational capabilities in translating digital data into business value within a project-based industry. From a practical perspective, the findings suggest that construction organisations should move beyond basic digitalisation and data collection to develop analytical competencies and organisational practices that support the effective use of data.

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