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Developing a Big Data Analytics Adoption Framework for the Construction Industry: A Grounded Theory Approach

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Abstract: Big data analytics (BDA) offers transformative potential for decision-making and operational efficiency in the construction industry, yet its adoption remains limited. This study addressed this gap by identifying key determinants and developing a comprehensive framework tailored to the industry's unique dynamics. Using a qualitative grounded theory approach, 16 semi-structured interviews were conducted among construction organisations to uncover inter- and intra-organisational factors influencing BDA adoption. The study outlined three progressive adoption stages of creating big data, big data buy-in and revolutionising through big data. The study further identifies seven critical determinants, with collaboration emerging as a pivotal enabler. Grounded in the technology-organisation-environment (TOE) framework, the proposed framework offered actionable guidance for construction organisations to navigate the adoption journey, from infancy to maturity. This study bridges data science and construction, advancing theoretical understanding and providing practical insights to foster digital transformation and establish a robust foundation for a data-driven construction industry.

Keywords: Big data analytics, Artificial intelligence, Construction industry, Grounded theory, TOE framework

INTRODUCTION

The construction industry is experiencing a digital transformation, driven by the rapid adoption of technologies such as drones, building information modelling (BIM) and sensors. Achieving effective end-to-end digitalisation throughout the construction lifecycle is critical for advancing big data analytics (BDA) within the industry. As a result, the construction sector generates vast volumes of structured and unstructured digital data, characterised by the three Vs of volume, velocity and variety (Elia et al., 2022). This exponential data growth provides a robust foundation for BDA innovation in the 21st century. In alignment with the National Construction Policy 2030, BDA advancements play a pivotal role in supporting the national goal of adopting data-driven approaches across construction processes.

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BDA's potential in the construction industry has been widely recognised, particularly in areas such as building automation, project risk management, construction bankruptcy prediction and construction safety prediction (Himeur et al., 2022; Owolabi et al., 2020; Ajayi et al., 2018; Chen, Lu and Liao, 2017; Alaka et al., 2015). Research also highlighted the application of BDA in improving profitability performance and construction waste prediction (Bilal and Oyedele, 2020; Chen, Lu and Liao, 2017). In terms of organisational application, recent studies have explored BDA capability assessments and the intention of construction firms to adopt BDA technologies (Chaurasia and Verma, 2020; Ngo, Hwang and Zhang, 2020; Atuahene, Kanjanabootra and Gajendran, 2018). These studies demonstrated the growing recognition of BDA's role in improving decision-making within the construction industry. As BDA has been developed to address specific construction applications in countries such as the United Kingdom and China, most of these analytics models remain conceptual and have yet to be fully operationalised for widespread use. In addition, the adoption of BDA in the construction industry remains limited, despite positive findings in these areas. Research on BDA adoption frameworks has revealed that there has been limited adoption progress among construction organisations (Regona et al., 2022; Ngo, Hwang and Zhang, 2020; Ismail, Bandi and Maaz, 2018).

Current adoption frameworks tend to be quantitative, relying heavily on statistical analyses of BDA adoption determinants at the organisational level. While useful for identifying correlations, these frameworks lack in-depth contextual understanding of how and why construction organisations adopt BDA. There is a paucity of research that investigated BDA adoption from a holistic understanding of "what", "why", "who", "when", and "how" of BDA integration within the diverse, dynamic environments of construction projects. On the other hand, successful BDA adoption in the construction industry heavily relies on data-driven decision-making, supported by large and comprehensive data access among construction organisations (Tan et al., 2023; Ngo, Hwang and Zhang, 2020). This presents a gap in the specific need for a BDA adoption framework that appraises the characterisation of BDA from the industry context, encompassing both inter- and intra-organisational levels. Attribution of specific BDA potentials and attributes at various BDA levels is crucial for providing comprehensive guidance to facilitate seamless BDA adoption.

Hence, this study addressed two objectives: (1) to explore key BDA adoption determinants related to BDA potentials in the construction industry and (2) to develop a BDA adoption framework to enhance understanding and improve the successful adoption of BDA among construction organisations. The framework outlined progressive stages of the BDA phenomenon, guiding organisations from infancy to maturity in their BDA adoption journey in developing countries. The strength of this study lies in its contribution to the establishment of the computer science knowledge domain within the construction industry context.

Big Data Analytics Potential Application in the Construction Industry

Originating from the data science domain, BDA challenges the traditional reliance on human experience by promoting a proactive, data-driven decision-making approach. Leveraging the three key data characteristics—volume, variety and velocity (3V)—BDA enhances the accuracy and comprehensiveness of decision-making processes. It is particularly effective in managing anticipated risks in areas such as project risk management, energy management, facilities management, wastewater management and project safety management and addressing bankruptcy or fraud issues before project commencement (Meng et al., 2022; Halttula, Haapasalo and Silvola, 2020; Owolabi et al., 2018; Koseleva and Ropaite, 2017; Alaka et al., 2015).

Beyond risk management, BDA's potentials extend to delivering new or enhanced services that complement the construction process. For instance, construction organisations with robust BDA capabilities can develop digital project cost databases, enabling them to offer data-driven services as a value addition. This not only supports operational efficiency but also creates new revenue streams for construction organisations.

Strategic Approach to Big Data Analytics Adoption

To support the strategic adoption of BDA, research has focused on developing BDA frameworks and the Big Data Maturity Model (BDMM). BDMM plays a pivotal role in guiding organisations through key aspects of BDA adoption, including making initial decisions, prioritising improvement measures, monitoring implementation progress and providing a structured roadmap to enhance BDA maturity. Table 1 summarises the critical determinants of BDA adoption identified across various research domains. Both the BDA framework and BDMM share a common foundation in BDA determinants to address organisational capabilities.

Table 1. Summary of BDA adoption determinants across BDA research areas

BDA Adoption Determinants	BDA Research Areas		Sources
	BDA Framework	BDMM	
Data	✓	✓	Comuzzi and Patel (2016); Dhanuka (2016); Atuahene, Kanjanabootra and Gajendran (2018); Ram, Afridi and Khan (2019); Chaurasia and Verma (2020); Ngo, Hwang and Zhang (2020); Yu, Liang and Wang (2020)
Technology	✓	✓	Atuahene, Kanjanabootra and Gajendran (2018); Nguyen (2018); Ram, Afridi and Khan (2019); Chaurasia and Verma (2020); Hatoum, Piskernik and Nassereddine (2020); Hausladen and Schosser (2020); Ngo, Hwang and Zhang (2020); Yu, Liang and Wang (2020); Aghimien et al. (2021)
Skills/People	✓	✓	Halper and Krishnan (2013); Nguyen (2018); Ram, Afridi and Khan (2019); Hausladen and Schosser (2020); Ngo, Hwang and Zhang (2020)
Financial investment	✓	✓	Halper and Krishnan (2013); Chaurasia and Verma (2020); Ngo, Hwang and Zhang (2020); Aghimien et al. (2021)
BDA strategy	✓	✓	Chaurasia and Verma (2020); Hatoum, Piskernik and Nassereddine (2020); Hausladen and Schosser (2020)
Power	✓	✓	Comuzzi and Patel (2016); Nguyen (2018); Chaurasia and Verma (2020); Ngo, Hwang and Zhang (2020); Yu, Liang and Wang (2020)

Data determinant focuses on managing and safeguarding data while addressing privacy concerns throughout the BDA process. As construction projects adopt technology, they generate vast volumes of both structured and unstructured data. Structured data is well-organised and easy to interpret, whereas unstructured data, such as web clickstreams and geolocation information, requires advanced analytical techniques. In developing countries, the construction industry emphasises digitalising construction processes and improving data management practices to enhance the quality and efficiency of data capture (Tan et al., 2023). Technology determinant identifies the physical and virtual tools that enable BDA, including hardware, software, mathematical algorithms and analytical platforms. The determinant prioritises security measures to protect BDA solutions while employing advanced analytics techniques to extract actionable insights. For the construction industry, adopting technology often means leveraging platforms to provide evidence-based decision-making capabilities. Skills determinant highlights the importance of technical and analytical expertise among construction professionals and data specialists. Essential skills for successful BDA implementation include coding, programming, system modelling and data analysis, combined with strong communication abilities to articulate insights effectively. Developing such talent is a cornerstone of successful BDA adoption (Mazzei and Noble, 2017).

BDA success also hinges on stable financial resources. Investments are required for technology procurement, setup costs, ongoing expenses, workforce development and training programmes. Adequate budget allocation across the different phases of implementation is critical to sustaining BDA initiatives (Alharthi, Krotov and Bowman, 2017; Verma and Bhattacharyya, 2017). BDA strategy emphasises aligning organisational resources to achieve BDA goals, with a critical emphasis on strong business cases and clear objectives (Hausladen and Schosser, 2020). Organisations can advance BDA development by focusing on critical business areas. The BDA strategy determinant involves using a roadmap as a mechanism to coordinate the process, from identifying data sequences to generating insights, establishing timelines, assigning responsibilities and setting overall milestones. Finally, power plays a crucial role in providing guidance and spearheading the big data vision. Strong management support provides a means to address resistance to BDA initiatives and secures commitment to investment in BDA (Chaurasia and Verma, 2020; Nguyen, 2018). The influence of power extends to shaping the organisation's BDA capabilities, particularly through top management involvement.

The adoption of BDA in the construction industry is shaped by four key aspects: (1) the unique characteristics of construction projects, (2) the size of construction organisations, (3) the dynamics of authoritative power and (4) the infancy of BDA in the sector. Construction projects are inherently unique and no two projects are identical. While they follow similar construction stages, they differ in factors such as geolocation and the composition of project teams. Additionally, most construction organisations are small to medium-sized, which poses challenges in making substantial investments in BDA (Kamal and Flanagan, 2012). In developing countries, BDA is still in its early stages, with current efforts primarily focused on automating data creation processes and improving data quality management (Veras, Renukappa and Suresh, 2022). In addition, technology adoption often occurs through top-down approaches. In contrast, developed nations tend to rely on proactive investments by private stakeholders (Goldstein, Fink and Ravid, 2022). These contextual differences have created varied environments for BDA adoption within the construction industry.

Theoretical Underpinning

The technology-organisation-environment (TOE) framework is a well-established theoretical model for studying technology and information systems adoption. In construction research, this framework has been utilised to explore factors driving BDA adoption and its strategic value. For instance, Ram, Afridi and Khan (2019) emphasised technological aspects, such as the integration of BDA with BIM and related technologies, while Chaurasia and Verma (2020) identified eight key factors influencing BDA adoption, tailored specifically to the architecture, engineering and construction services. This study adopted the TOE framework due to its robust theoretical foundation, which enables a comprehensive analysis of the determinants across technological, organisational and environmental dimensions. This approach is particularly valuable for enhancing BDA adoption capabilities at the industry level. The TOE framework has been widely applied in technology adoption research, offering insights at both inter- and intra-organisational levels (Borgman et al., 2013; Baker, 2012). The application of the TOE framework in this study is outlined as follows:

1. Technology: This dimension examined both external technologies available in the construction market and the internal technologies currently employed by organisations.
2. Organisation: This dimension focused on organisational characteristics and resources, including firm size, top management support, managerial structure, workforce quality, information-sharing culture and the organisation's absorptive capacity.
3. Environment: This dimension considered the broader business context, encompassing industry structure, access to resources, institutional pressures and the influence of business partners.

METHODOLOGY

This study adopted the qualitative grounded theory approach to establish the construction industry BDA framework. The approach is well-suited for uncovering emerging constructs in complex, underexplored areas like BDA. The grounded theory enables the organic emergence of concepts from data, ensuring that the framework reflects the practical realities at inter- and intra-organisational dynamics of the construction sector. This method has been successfully applied to mechanise BDA application in healthcare and education (Jia, 2024; Wang, Ye and Liu, 2023).

The framework development followed a five-stage research process. Stage 1 involved an extensive literature review on BDA adoption, identifying five key determinants that informed the interview guide (as shown in Table 1). Stage 2 involved a pilot study with three academic and industry experts. The finalised guide included three sections: (1) participants' background and BDA project involvement, (2) open-ended questions on BDA potential in construction and (3) suggestions for enhancing BDA adoption at organisational and industry levels.

Stage 3 of the research involved data collection through semi-structured interviews with 16 participants, selected using the snowball sampling method. This method was chosen due to its suitability for identifying individuals with shared expertise and experience in BDA development within the construction industry, especially given the nascent stage of BDA adoption in the Malaysian construction sector. Participants were required to have at least five years of experience and prior involvement in BDA to ensure credibility.

The scope of this study focused on the development, adoption and advancement of BDA pursued by the Malaysian authorities (CIDB [Construction Industry Development Board] Malaysia, 2020). The research covered a wide range of stakeholders involved in BDA, including contractors, developers, public agencies, consultants, academia and software firms. These participants represented both inter- and intra-organisational levels of the construction sector, providing a comprehensive view of the industry's BDA landscape (as shown in Table 2).

Table 2. Participants' credentials and details

Participant	Position	Years of Experience	Profession	Construction Organisation	Framework Validator
P1	Senior general manager	More than 10 years	Quantity surveyor	Public agency	
P2	Senior lecturer	More than 10 years	Quantity surveyor	Academia	
P3	Senior project manager	More than 20 years	Engineer	Consultant	
P4; P5	Assistant manager	More than 10 years	Quantity surveyor	Public agency	
P6	Cost manager	More than 20 years	Quantity surveyor	Developer	Yes
P7	Senior project executive	More than 10 years	Engineer	Consultant	

(Continued on next page)

Table 2. *Continued*

Participant	Position	Years of Experience	Profession	Construction Organisation	Framework Validator
P8	Senior general manager	More than 20 years	Quantity surveyor	Public agency	Yes
P9	Senior project manager	More than 10 years	Engineer	Contractor	
P10	Assistant manager	More than 5 years	Project manager	Public agency	
P11	Senior general manager	More than 20 years	Engineer	Public agency	
P12	Assistant manager	More than 10 years	Quantity surveyor	Public agency	
P13	Associate professor	More than 20 years	Engineer	Academia	Yes
P14	Information technology manager	More than 20 years	Engineer	Developer	
P15	Senior business development manager	More than 20 years	Technology professionals	Software firm	Yes
P16	Project executive	More than 20 years	Technology professionals	Software firm	

Interviews were conducted in Kuala Lumpur, Malaysia. Each session lasted approximately two hours. To ensure diverse perspectives, participants were selected from various segments of the construction industry, including large-scale infrastructure projects, residential developments and commercial construction. This heterogeneous sample helped minimise potential biases and provided a broad view of BDA implementation across different types of construction projects and companies. The snowball sampling was employed. Though it can introduce bias, steps were taken to mitigate this by selecting participants from varied professional backgrounds, ensuring the research captured a diverse set of viewpoints. The findings offered insights into the current state of BDA in the construction industry, challenges faced and the specific needs for further development of BDA adoption frameworks.

Stage 4 utilised Charmaz's (2006) constructivist grounded theory method to develop the BDA adoption framework. This method emphasised the researcher's active role in interpreting data to construct a nuanced understanding of BDA adoption in construction. The process began with open coding, where data were analysed line-by-line using NVivo software, guided by the "perceived benefit" principle to identify BDA potential and the TOE framework to uncover adoption determinants. During axial coding, the open codes were refined through reflexive questions (e.g., what, why, how), with constant comparison across data sources, codes and theoretical samples. This iterative process yielded 177 codes that captured the dimensions, properties and characteristics of the BDA phenomenon in the construction industry. Theoretical saturation was achieved by the 12th interview, as no new themes or insights emerged (Glaser, 1978). Figure 1 illustrates the NVivo coding environment.

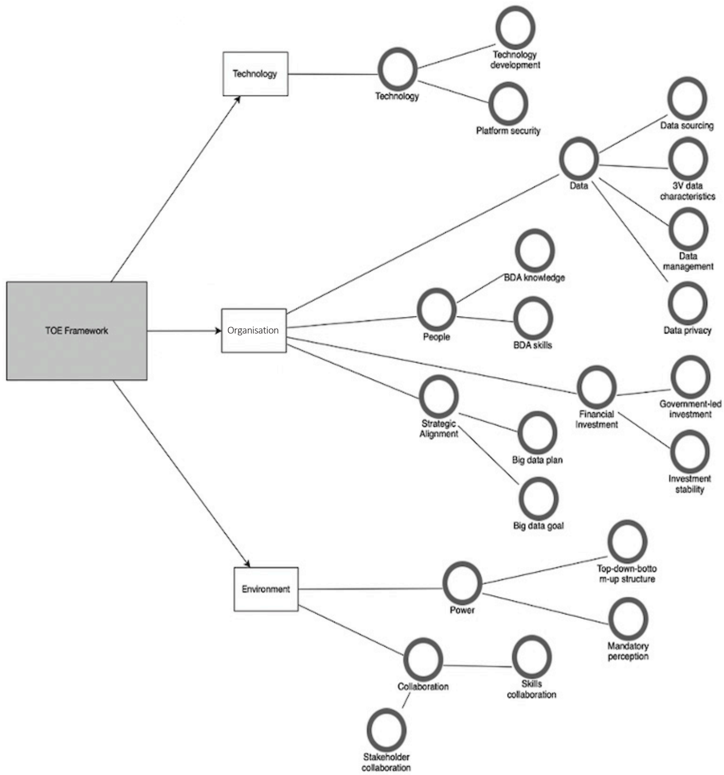

Figure 1. Codes on BDS determinants using NVivo12 software

In selective coding, the paradigm model was applied as an analytic tool to construct the BDA phenomenon. This model facilitated the integration of axial codes into a cohesive understanding of the relationships among context, conditions, intervening factors and consequences. It enabled the creation of the BDA adoption framework by identifying how BDA potentials and determinants interact. Figure 2 shows the selective coding process, which formed the foundation of the framework.

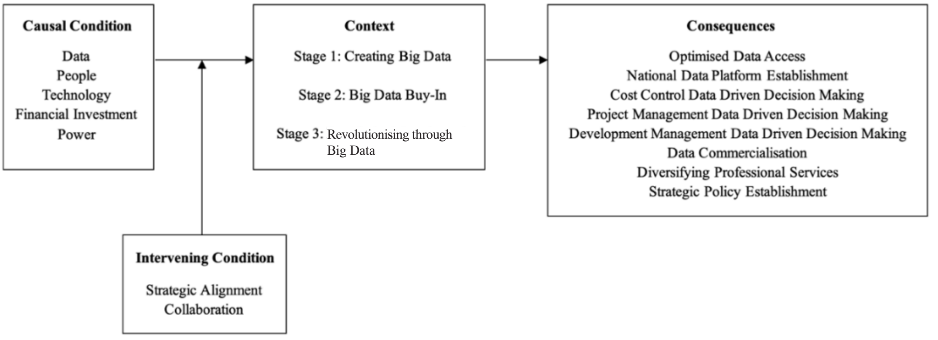

Figure 2. Paradigm model as the grounding basis of BDA adoption framework

Stage 5 involved validating the framework through a focus group discussion with industry practitioners from data science and construction, selected from the participant pool for their extensive experience (as shown in Table 2). Validation focused on two areas: (1) the relevance of BDA stages in defining the construction industry's BDA phenomenon and (2) the applicability of adoption determinants to the identified potentials at each stage. The validation yielded positive results with no major revisions required. Suggestions from P6 and P15 led to refining the "business collaboration" code to "stakeholders' collaboration" to better reflect the diverse roles of construction stakeholders. This refinement enhanced the framework's ability to support complex BDA model development in construction.

The Construction Industry BDA Adoption Framework

The BDA adoption framework for the construction industry consists of three sequential stages: (1) Creating big data, (2) Big data buy-in and (3) Revolutionising through big data. Figure 3 outlines the key adoption determinants and potential BDA applications in the BDA adoption framework. The framework offers a clear roadmap for construction organisations to progress from initial adoption to full maturity. The detailed findings supporting this framework are presented in Table 3.

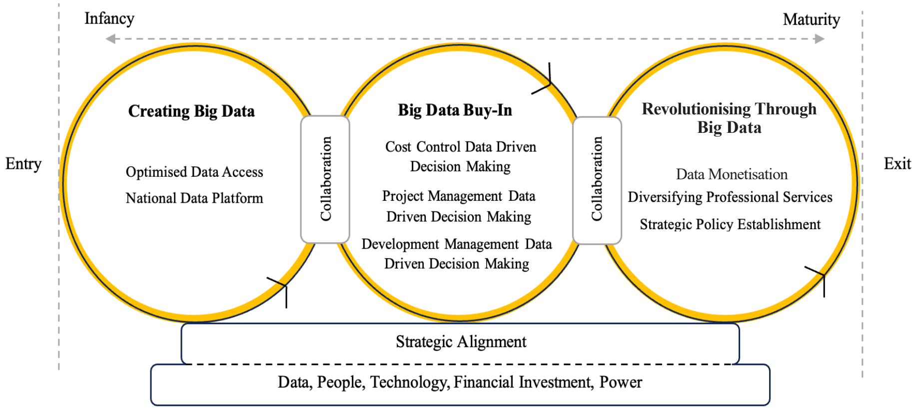

Figure 3. The construction industry BDA adoption framework

The "Creating big data" stage serves as the foundational phase, emphasising the establishment of a national data platform to enhance data accessibility and transparency. At this stage, organisations focus on timely access to large volumes of diverse, high-quality data, setting the groundwork for subsequent analytics efforts. The "Big data buy-in" stage signifies a deeper integration of BDA into organisational workflows. Key objectives include embedding BDA to improve decision-making processes and operational efficiency. Central to this stage is the development of a unified platform for hosting, integrating and analysing data, enabling advanced data-driven capabilities in areas like cost control, project management and construction development management. The final "Revolutionising through big data" stage involves organisations fully exploiting advanced analytics to generate new business value. This stage encompasses initiatives such as data monetisation, service diversification and the creation of strategic policies that position data as a core business asset.

Table 3. Details of the construction industry BDA adoption framework context

BDA Determinants	**Construction Industry BDA Adoption Framework Context**		
	Stage 1: Creating Big Data	**Stage 2: Big Data Buy-In**	**Stage 3: Revolutionising Through Big Data**
Data		Data Sourcing and Characteristics	
(P1; P2; P3; P4; P5; P6; P7; P8; P9; P10; P11; P12; P13; P14; P15; P16)	1. Limited data availability 2. Poor data quality 3. Lack of data standardisation 4. Volume and variety BDA characteristics	1. Inter-organisational data sourcing among construction stakeholders 2. Technical construction data sourcing of building material price, labour wage, machinery and equipment purchase price 3. Progressive sourcing of volume and variety BDA characteristics 4. Velocity BDA characteristics through the automated data creation process	1. Optimum maximisation of 3V BDA characteristics 2. Symbiotic internal and external data sourcing with data from other industries relevant to BDA goals 3. Seamless flow of data transactions
		Data Management	
	Manual data management	1. Initiation of standardised construction data architecture for industry-wide application 2. Semi-automated data management process (automated data capture with extended data validation process) 3. Manual construction professionals to manage BDA insights relevance	1. National industry-wide standardised data architecture adoption 2. Fully automated BDA solutions with professional bodies and local authorities overseeing data governance
		Data Privacy	
	Highly trust dependency	1. Legal approach (binding private and confidential agreement) to maintain data privacy	Specific construction industry data policy establishment as a legal measure

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Table 3. *Continued*

BDA Determinants	**Construction Industry BDA Adoption Framework Context**		
	Stage 1: Creating Big Data	**Stage 2: Big Data Buy-In**	**Stage 3: Revolutionising Through Big Data**
		2. Requires a definitive data boundary	
People (P1; P2; P3; P4; P7; P8; P10; P13)		Big Data Knowledge	
	Stakeholders' awareness of BDA concept and potential	–	1. Construction professionals' effective BDA usage 2. Construction professionals' active participation in BDA innovation 3. BDA innovation based on organisation data resource, BDA skills and technology capability
		Skills	
	1. Data management skills on digitalisation, data processing and accessibility and data storage 2. Programming skills in data sourcing and migration	1. Construction professionals upskilling to increase construction decision making 2. Analytics skills outsourcing and data visualisation	1. Emergence of BDA skills or data scientists among construction professionals 2. Less reliance on outsourced skills to advance BDA
Technology (P5; P6; P9; P11; P15; P16)		Technology Development	
	Silo technology platform	1. Expansion towards an end-to-end data system 2. Artificial intelligence (AI) technique exploration (descriptive and diagnostic analytics) 3. Technology infrastructure support (strong, fast and widely available internet connection)	AI exploration to support automated BDA solutions, analysis of structured data (financial data and bill of quantities) and unstructured data (BIM models and video of construction site progress)

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Table 3. *Continued*

BDA Determinants	**Construction Industry BDA Adoption Framework Context**		
	Stage 1: Creating Big Data	**Stage 2: Big Data Buy-In**	**Stage 3: Revolutionising Through Big Data**
		Platform Security	
	Inhouse data server and scepticism on cloud data storage	1. Openness towards cloud data storage to cope with data growth 2. Security emphasis managing data leaks and improved data interoperability	1. Construction professionals are knowledgeable about the technical aspects of big data security 2. Construction industry-specific BDA security framework/ BDA solution security with ISO measures
		Investment Nature	
Financial investment (P1; P8; P10; P12; P15; P16)	1. Government-led investment 2. Adhoc investment 3. Large investment in pre-process and digitalise data skills	1. Construction organisation BDA investment 2. Preference for inhouse BDA solution	1. Consistent and stable BDA investment 2. Monetary form of BDA value creation through mature data maximisation
Power		Role of Power	
(P1; P2; P3; P4; P5; P6; P7; P8; P9; P10; P11; P12; P13; P14; P15)	1. Top-down government's "mandatory" impression to instigate big data demand, remove bureaucracy and "red tape" in data sharing 2. Top-down government data standardisation	1. Top management advocating BDA in private organisations with voluntary BDA adoption 2. BDA reinforcement, such as recognition, award or monetary reward, to improve BDA adoption	A combination of top-down and bottom-up synergistic relationship between BDA users (construction professionals) and top management on BDA innovation

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Table 3. *Continued*

BDA Determinants	**Construction Industry BDA Adoption Framework Context**		
	Stage 1: Creating Big Data	**Stage 2: Big Data Buy-In**	**Stage 3: Revolutionising Through Big Data**
Strategic alignment (P2; P3; P5; P7; P12; P15; P16)		Big Data Goal	
	1. Short-sighted big data goals 2. Too focused on the technical aspects of construction data creation, management across the construction project process	1. Generic but clear big data goal 2. Forward-looking and integrative big data goal	Consortium approach to big data goals at the inter- and intra-industry levels
		Big Data Plan	
	Compartmentalised, inarticulate and lacking strategic BDA direction	1. Strategic BDA plan on BDA development, BDA adoption and BDA advancement 2. The need for specific data governance for the construction sector at the industry level to manage ethical and facilitated BDA advancement	Modification of the conventional construction business model to incorporate BDA value creation
Collaboration (P2; P5; P6; P9; P11; P12; P13; P15; P16)	Skills Collaboration		
	1. Diverse yet niche skills collaboration (statistics, machine learning, AI, data visualisation, programming and construction technical skills) to improve communication uniformity 2. Increase the construction professionals' BDA learning curve in understanding computer science technicalities		
	Stakeholders Collaboration		
	1. Multi-perspective collaboration (e.g., between developers, technology providers, local authorities, consultants, contractors and suppliers) 2. Increase data sourcing capability and optimise BDA model 3. Increase inter-industry collaboration		

Table 4 highlights the criteria for transitioning between these stages. The shift from the "Creating big data" stage to the "Big data buy-in" stage is facilitated by three factors: stakeholder engagement, compliance with data-sharing standards and the adoption of basic analytics. These elements ensure alignment among key stakeholders, establish secure data-sharing frameworks and enable organisations to begin extracting actionable insights.

Table 4. Transition criteria between BDA adoption framework stages

BDA Stage	Key Activity	Transition Criteria
Creating big data	1. Establishing a national data platform 2. Improving data accessibility	1. Stakeholder engagement 2. Data sharing compliance 3. Basic data analytics adoption
Big data buy-in	1. Integrating data into the workflow 2. Centralised data analysis	1. Advanced data analytics adoption 2. Cross-functional collaboration Alignment with strategic goals
Revolutionising through big data	1. Maximising analytics insights 2. Monetisation	1. New revenue streams 2. Diversification of services 3. Full-scale data automation

Progressing to the "Revolutionising through big data" stage depends on achieving critical milestones, including the creation of new revenue streams, diversification of services and automation of analytics. Organisations at this stage leverage predictive analytics and innovative decision-making to develop data-centred business models. Collaboration among stakeholders, particularly government agencies, construction firms and technology providers, is essential for advancing to this stage. These partnerships integrate construction expertise with cutting-edge technologies, such as data science, machine learning and AI, expediting the automation of data processes and unlocking new opportunities for business growth.

DISCUSSION

Data

In the field of data science, data analytics techniques have evolved to maximise the 7V (i.e., volume, velocity, variety, variability, veracity, value and visualisation) data characteristics to enhance the value of BDA insights (Dhanda, 2022; Monino, 2021). However, in the construction industry, BDA applications primarily rely on the 3V (i.e., volume, velocity and variety) data characteristics in structured and unstructured forms. Maximising these 3V characteristics does not necessarily guarantee valuable BDA insights for construction organisations. Instead, meaningful insights are often achieved by focusing on the effective utilisation of the three dimensions (Ngo, Hwang and Zhang, 2020).

Findings from this study revealed that generating valuable BDA insights in the construction industry depended on understanding the complex, multi-layered relationships among stakeholders to deliver multi-perspective data analytics (P4). While the potential of the 7V data cannot be overlooked, construction organisations can derive significant value from collecting comprehensive project lifecycle data (i.e., from pre-construction to post-construction phases) sourced from diverse stakeholders, such as contractors, developers, consultants and local authorities.

Generating quality and accurate BDA insights requires robust data management processes, including data collection, cleaning, verification, storage and analysis. However, the construction industry faced persistent challenges due to poor data standardisation. For instance, P16 noted, "We rely on professional bodies to ensure the generation of valuable insights". Although data creation guidelines, such as the Standard Method of Measurement (SMM), exist, adherence to these standards was inconsistent. Construction professionals frequently deviated from established guidelines to suit organisational preferences, leading to data quality issues. Therefore, ensuring compliance with standard guidelines is critical for implementing effective data management protocols, enhancing data quality and optimising BDA insights.

In terms of data privacy, construction organisations rely on trust and good faith rather than technological solutions such as blockchain (Kiu, Chia and Wong, 2020). Mandatory data sharing was aligned with the national agenda, but organisations "manually remove confidential data such as project name and client name" (P6) to mitigate data privacy concerns. Concerns regarding data protection hinder construction organisations' data sharing efforts. P4 shared, "We do not feel comfortable sharing data because we do not know how the data will be". In BDA research, the establishment of comprehensive data policies has been shown to facilitate a secure and efficient data-sharing environment (Dhanda, 2022; Blasimme et al., 2018). Therefore, formalising data policies that clearly define data ownership, sharing boundaries and trading mechanisms is essential. Such policies can help mitigate privacy concerns, foster trust among stakeholders and enable effective and sustainable BDA adoption in the construction industry.

People

People are a critical resource for advancing BDA adoption, particularly through their knowledge and skills in data analytics. Understanding BDA knowledge, such as "big data concept, what it needs and a clear picture of what it can do" (P1, P4 and P13), provided a foundational framework for effective communication between construction organisations and platform providers. Moreover, the widespread adoption of BDA underscores the importance of improving data literacy among construction professionals (Aghimien et al., 2021; Atuahene, Kanjanabootra and Gajendran, 2018). Data literacy enhances "capability to strategically use data, analyse data and use fitting big data insights" (P14). The findings indicated that fostering BDA knowledge helps bridge the gap between deep technical expertise in construction and advanced technological knowledge, driving both adoption and expansion of BDA.

During the early stages of BDA, construction organisations often tend to rely on data science skills overly, "We mostly hire them because these skills are not our domain" (P11). However, the study findings emphasised the equal importance of construction professionals' technical expertise and data science skills for BDA advancement. This is because the successful development of BDA models depends on construction professionals' ability to source relevant data, design effective data cleaning protocols and select appropriate analytics techniques to generate meaningful insights. Contrary to fears of obsolescence, BDA technologies expand rather than diminish the skill set of construction professionals. To address this evolving landscape, this study advocated for redefining the role of data scientists within the construction domain. Equipping construction professionals with data science competencies is critical for enabling higher-level BDA applications. Data science competencies, such as "machine learning and AI skills to train data for higher predictive and prescriptive analytics" (P16, P17 and P18), "data visualisation to construction users' interpretation" (P2, P5 and P7) and "programming as the most basic skill" (P6, P8 and P11), were seen as the BDA agenda in this industry.

Technology

Technology is a critical factor for construction organisations to advance BDA adoption. In developing countries, manual data management processes are still common, but the integration of BIM simplifies the process through automated real-time data extraction. P8 mentioned, "Real-time data with limited hassle is when BIM is in the picture". BIM is viewed as a foundational technology that supports BDA progress. Interoperability between digitalisation platforms was found critical to manage complex yet seamless BDA solutions (Zhang et al., 2017). As such, it is crucial for "BDA technology to be flexible" (P2, P6 and P8). Flexibility refers to the ability to integrate various digital tools such as "Aconex, Procore and Speedbrick" (P11) and manage "plug-ins to cater future BDA features expansion" (P1 and P14).

Cloud storage technology is vital for facilitating real-time data access while efficiently managing the growth of data in a cost-effective manner (Agrawal and Tapaswi, 2019). However, this study revealed that in the early stages of BDA adoption, construction organisations tend to favour physical data servers due to concerns about data security. This preference stemmed from the limited exploration of available BDA security technologies in the construction sector and the lack of clear distinctions between security and privacy issues in BDA literature (Veras, Renukappa and Suresh, 2022; Yousif et al., 2021; Yu, Liang and Wang, 2020). Participants expressed that "physical data server is better. It is harder for others to hack into our data if the server is here in our office" (P6 and P9), highlighting the perceived security benefits of on-site data storage.

As data volumes continue to rise, construction organisations consider cloud-based solutions as a viable alternative in Stage 2 of BDA adoption. By Stage 3, the findings align with Yang, Xiong and Ren (2020) on the necessity for an "industry endorsed security framework" (P5) or "big data system security with International Organisation for Standardisation (ISO) measures" (P13). The establishment of reliable BDA security technologies becomes crucial to mitigate risks such as data hacking and leakage, ensuring safe and secure data management as the industry moves toward full BDA integration.

Financial Investment

Typically, BDA investments are led by business organisations (Manyika et al., 2011). The construction sector, particularly in Malaysia, often relies on government-led initiatives through grants and consortium collaborations. On average, BDA requires USD6 million investment (Alharthi, Krotov and Bowman, 2017). BDA developments are often tailored into a series of "mini-packages to meet investment capability" (P3). This is because investment for BDA adoption far exceeds the construction organisation's investment capabilities, as these organisations are predominantly small and medium in scale. Thus, stable and consistent BDA investment ensures continuity in building a comprehensive BDA model for construction organisations "to reap the full BDA potential" (P3).

The findings in this study offered a dual perspective on BDA financial investment. Unlike technologies such as sensors, drones, or BIM, BDA adoption requires financial investment but presents an immense opportunity for revenue generation. Participants noted that construction organisations gain "monetary form of big data value creation through organisation's big data monetisation" (P6, P15 and P18). In the Malaysian context, the Building Cost Information Services Malaysia (BCISM) serves as a national-level data platform designed to monetise real-time and high-quality construction data. Through BDA, BCISM capitalises on competitive data value and limited data availability by offering subscription packages to access construction cost data.

Power

Power refers to the influential position of government entities and top managers within construction organisations, both at intra- and inter-organisational levels. As P4 noted, "I see the potential of big data. But that does not mean I will adopt this expensive technology. And why should I do that, because as for now, I still make money. We are comfortable in this position. If the government gives an incentive for big data, I am sure to be one of the first to use it". This highlights how power dynamics, particularly from government incentives or recognition, play a crucial role in stimulating demand for BDA adoption. The impact of power is further evident in the complexities of navigating bureaucracy related to data sharing. P12 explained, "The way we operate, we have many layers. Our big data project deals with the authority, professional bodies and developers, where they have a specific confidential agreement for sharing data. ...What we did was work closely with the key person. This saves time and all the red tape".

This study provided evidence of the benefits of a symbiotic alliance between top-down and bottom-up approaches to BDA adoption. P13 emphasised construction professionals' proficiency in handling construction big data as an analytical skill to facilitate BDA advancement. Analytical skills were considered "the main turning point" (P2), triggering bottom-up adoption in Stage 2. Additionally, guidance from top managers was vital for ensuring that proposed BDA advancements align with organisational strategies. The collaborative relationship between bottom-up and top-down efforts ultimately reduces the need for rigid top-down directives (Mikalef et al., 2019).

Strategic Alignment

This study emphasised the importance of establishing clear, forward-looking BDA goals to ensure effective communication across organisational layers. P6 highlighted "BDA projects mostly suffer short-sighted big data goals, too focused on technical aspects, initiative compartmentalisation and non-strategic big data plan". In contrast, P13 stressed the need for integrated, strategic BDA goals and plans, aligning BDA development, adoption and advancement with business strategies. To manage BDA effectively, tools such as SWOT analysis, business models, change matrices and balanced scorecards are essential. A strong strategic management approach is crucial for the success of BDA adoption (Dutta and Bose, 2015; LaValle et al., 2011). As BDA adoption matures, traditional business plans must be updated to accommodate BDA within existing work processes and resource utilisation. P6 added, "With the potential of generating revenue from big data, I think we cannot rely on our current business practice", suggesting the need to reassess current construction business practices in light of BDA revenue-generating potential.

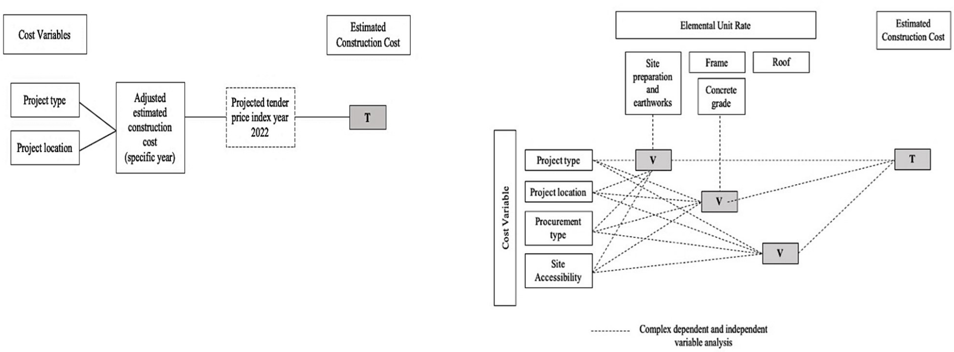
Consistent with Walls and Barnard (2020), the data governance mechanism is critical to facilitate successful BDA adoption. Despite the tremendous value of BDA insights, participants raised concerns, such as "how do we make sure ethical use of data?" (P11) and "What if BDA insights are misleading?" (P14). Given the complex stakeholder relationships and project-based nature of the construction industry, effective data governance is vital. It ensures the establishment of clear roles, processes and policies to foster an environment conducive to BDA. The importance of data governance extends beyond ownership issues. Poor data governance can lead to legal, financial and social repercussions, affecting both organisations and society at large (Janssen et al., 2020).

Collaboration

Using the qualitative grounded theory methodology, this study identified collaboration as a key determinant for BDA adoption in the construction industry. Collaboration enables the strategic utilisation of BDA resources across construction organisations and supports smooth transitions between the stages of BDA adoption. Aligning with Günther et al. (2017), the study indicated that collaboration significantly accelerates the progression towards mature BDA adoption stages.

The findings in this study also aligned with Miller (2014) on the significance of collaboration to close the BDA skills gap. A skills collaboration strategy involves combining various specialised skills, under two domains: construction technical skills (i.e., quantity surveyors, engineers, architects) and BDA skills (i.e., statistical, machine learning, AI programming). P11 expressed time issues, "Wasted for them to understand what we want in the first place. The problem is meeting that point and we had to make changes again and again". Engaging in early skills collaboration helps construction organisations learn BDA more efficiently and speeds up adoption. This collaboration also addresses the shortage of big data skills within the industry.

This study highlighted the positive impact of stakeholder collaboration on BDA adoption and progression. Collaboration between consultants, contractors, clients and local authorities enhances the value of BDA insights by sourcing multi-perspective data, offering analytics of various perspectives and concerns. Figure 4 illustrates two BDA projects, demonstrating how different levels of stakeholder collaboration impact the complexity of the BDA model developed. A higher degree of collaboration leads to more complex models that account for variables such as project type, location, procurement methods and site accessibility, ultimately producing more comprehensive and valuable insights to support the construction project estimating process.



Big data model with minimal stakeholders' collaboration

Big data model with high stakeholders' collaboration

Figure 4. The different levels of stakeholders' collaboration impact on the complexity of the big data model

Stakeholders' collaboration also extends to inter-industry diversification strategies. P14 mentioned, "I see that my company can diversify through inter-industry collaboration by integrating weather data or quantification software". This collaboration strategy allows businesses to seamlessly access relevant data sources within existing big data frameworks (Balakrishna and Thirumaran, 2020), enabling multivariate data analytics to maximise the generation of valuable BDA insights.

CONCLUSION AND RECOMMENDATION

This study identified three stages of the BDA phenomenon in the construction industry. The two-stage coding process in qualitative grounded theory allowed this study to critically appraise the “Creating big data”, “Big data buy-in” and “Revolutionising through big data” stages, delineating BDA infancy to maturity in the construction industry. The construction industry BDA adoption framework outlines seven determinants as key capabilities to support construction organisations’ BDA adoption. Grounded in the TOE framework, this study revealed collaboration as an important determinant in facilitating BDA adoption.

In terms of the study’s practical implications, several actionable steps for construction organisations and policymakers to enhance BDA adoption may be suggested. For construction companies, prioritising collaboration between construction and data science experts can bridge the knowledge gap and facilitate the integration of BDA. Construction organisations, such as developers and contractors, should invest in building cross-functional teams to drive BDA initiatives and foster partnerships with technology providers to gain access to advanced analytics tools. In addition, policymakers should consider implementing data-sharing frameworks and incentivising collaboration across the construction sector to accelerate BDA adoption. For example, public-private partnerships could be established to fund the development of a national data platform, ensuring that SMEs can also benefit from BDA.

This study is limited in its scope to the Malaysian construction industry, which may not fully represent the challenges faced by other regions or developed countries. The unique economic, regulatory and technological landscape of Malaysia may impact the generalisability of the findings. To enhance the generalisability of the framework, future research could focus on testing its applicability in other developing countries, as well as in developed markets with more mature digital infrastructures. Longitudinal studies could also provide valuable insights into the long-term impacts of BDA adoption on construction organisations and their ability to innovate over time.

This study presents a unique foundation for bridging the understanding of BDA knowledge from the data science domain to the practical realities of the construction industry using qualitative methodology. The study extends the knowledge of established generic BDMMs and co-constructs an understanding between big data as technology, with an incremental value to organisations. To further advance BDA, future studies should also explore the mechanisation of data security, privacy and governance in construction organisations, ensuring trust and commitment to BDA initiatives.

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REFERENCES

Aghimien, D., Ikuabe, M., Aigbavboa, C., Oke, A.E. and Shirinda, W. (2021). Unravelling the factors influencing construction organisations' intention to adopt big data analytics in South Africa. *Construction Economics and Building*, 21(3): 262–281. https://doi.org/10.5130/AJCEB.V21I3.7634

Agrawal, N. and Tapaswi, S. (2019). Defense mechanisms against DDoS attacks in a cloud computing environment: State-of-the-art and research challenges. *IEEE Communications Surveys and Tutorials*, 21(4): 3769–3795. https://doi.org/10.1109/COMST.2019.2934468

Ajayi, A., Oyedele, L., Delgado, J.M.D., Akanbi, L., Bilal, M., Akinadé, O. and Olawale, O. (2018). Big data platform for health and safety accident prediction. *World Journal of Science, Technology and Sustainable Development*, 16(1): 2–21. https://doi.org/10.1108/WJSTSD-05-2018-0042

Alaka, H., Oyedele, L., Bilal, M., Akinadé, O., Owolabi, H. and Ajayi, S. (2015). Bankruptcy prediction of construction businesses: Towards a big data analytics approach. In *2015 IEEE First International Conference on Big Data Computing Service and Applications*. Piscataway, NJ: The Institute of Electrical and Electronics Engineers (IEEE), 347–352. https://doi.org/10.1109/BigDataService.2015.30

Alharthi, A., Krotov, V. and Bowman, M. (2017). Addressing barriers to big data. *Business Horizons*, 60(3): 285–292. https://doi.org/10.1016/j.bushor.2017.01.002

Atuahene, B., Kanjanabootra, S. and Gajendran, T. (2018). Towards an integrated framework of big data capabilities in the construction industry: A systematic literature review. In C. Gorse and C.J. Neilson (eds.), *Proceeding of the 34th Annual ARCOM Conference*. Belfast: Association of Researchers in Construction Management, 547–556.

Baker, J. (2012). The technology-organization-environment framework. In Y. Dwivedi, M. Wade and S. Schneberger (eds.), *Information Systems Theory: Integrated Series in Information Systems*. New York: Springer, 231–245. https://doi.org/10.1007/978-1-4419-6108-2_12

Balakrishna, S. and Thirumaran, M. (2020). Semantic interoperability in IoT and big data for health care: A collaborative approach. In V.E. Balas, V.K. Solanki, R. Kumar and M. Khari (eds.), *Handbook of Data Science Approaches for Biomedical Engineering*. Amsterdam: Elsevier, 185–220. https://doi.org/10.1016/B978-0-12-818318-2.00007-6

Bilal, M. and Oyedele, L.O. (2020). Big data with deep learning for benchmarking profitability performance in project tendering. *Expert Systems with Applications*, 147(1): 133194. https://doi.org/10.1016/j.eswa.2020.113194

Blasimme, A., Fadda, M., Schneider, M. and Vayena, E. (2018). Data sharing for precision medicine: Policy lessons and future directions. *Health Affairs*, 37(5): 702–709. https://doi.org/10.1377/hlthaff.2017.1558

Borgman, H.P., Bahli, B., Heier, H. and Schewski, F. (2013). Cloudrise: Exploring cloud computing adoption and governance with the TOE framework. In R.H. Sprague (ed.), *46th Hawaii International Conference on System Sciences (HICSS)*. Piscataway, NJ: IEEE, 4425–4435. https://doi.org/10.1109/HICSS.2013.132

Charmaz, K. (2006). *Constructing Grounded Theory: A Practical Guide Through Qualitative Analysis*. California: SAGE Publications.

Chaurasia, S. and Verma, S. (2020). Strategic determinants of big data analytics in the AEC sector: A multi-perspective framework. *Construction Economics and Building*, 20(4): 63–81. https://doi.org/doi.org/10.5130/AJCEB.v20i4.6649

Chen, X., Lu, W. and Liao, S. (2017). A framework of developing a big data platform for construction waste management: A Hong Kong study. In Y. Wu, S. Zheng, J. Luo, W. Wang, Z. Mo and L. Shan (eds.), *Proceedings of the 20th International Symposium on Advancement of Construction Management and Real Estate*. Singapore: Springer, 1069–1076. https://doi.org/10.1007/978-981-10-0855-9_94

CIDB (Construction Industry Development Board) Malaysia. (2020). *Construction 4.0 Strategic Plan (2021–2025): Next Revolution of the Malaysian Construction Industry*. Kuala Lumpur, Malaysia: CIDB Malaysia.

Comuzzi, M. and Patel, A. (2016). How organisations leverage big data: A maturity model. *Industrial Management and Data Systems*, 116(8): 1468–1492

Dhanda, N. (2022). Big data storage and analysis. In M. Niranjanamurthy, H.K. Gianey and A.H. Gandomi (eds.), *Advances in Data Science and Analytics: Concepts and Paradigms*. New Jersey: Wiley, 293–312. https://doi.org/https://doi.org/10.1002/9781119792826.ch13

Dhanuka, V. (2016). Hortonworks big data maturity model: The strategic path to accelerating business transformations. *Hortonworks White Paper*, March. Available at: https://hortonworks.com/wp-content/uploads/2016/04/Hortonworks-Big-Data-Maturity-Assessment.pdf

Dutta, D. and Bose, I. (2015). Managing a big data project: The case of Ramco Cements Limited. *International Journal of Production Economics*, 165: 293–306. https://doi.org/10.1016/j.ijpe.2014.12.032

Elia, G., Raguseo, E., Solazzo, G. and Pigni, F. (2022). Strategic business value from big data analytics: An empirical analysis of the mediating effects of value creation mechanisms. *Information and Management*, 59: 103701. https://doi.org/10.1016/j.im.2022.103701

Glaser, B.G. (1978). *Theoretical Sensitivity: Advances in Methodology of Grounded Theory*. California: Sociological Press.

Goldstein, A., Fink, L. and Ravid, G. (2022). A cloud-based framework for agricultural data integration: A top-down-bottom-up approach. *IEEE Access*, 10(4): 88527–88537. https://doi.org/10.1109/ACCESS.2022.3198099

Günther, W.A., Mehrizi, M.H.R., Huysman, M. and Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *Journal of Strategic Information Systems*, 26(3): 191–209. https://doi.org/10.1016/j.jsis.2017.07.003

Halper, F. and Krishnan, K. (2013). TDWI big data maturity model guide: Interpreting your assessment score. Available at: https://tdwi.org/whitepapers/2013/10/tdwi-big-data-maturity-model-guide.aspx

Halttula, H., Haapasalo, H. and Silvola, R. (2020). Managing data flows in infrastructure projects: The lifecycle process model. *Journal of Information Technology in Construction*, 25: 193–211. https://doi.org/10.36680/j.itcon.2020.012

Hatoum, M.B., Piskernik, M. and Nassereddine, H. (2020). A holistic framework for the implementation of big data throughout a construction project lifecycle. In K. Tateyama, K. Ishii and F. Inoue (eds.), *Proceedings of the 37th International Symposium on Automation and Robotics in Construction (ISARC 2020).* Kitakyushu, Japan: International Association on Automation and Robotics in Construction, 1299–1306. https://doi.org/10.22260/ISARC2020/0178

Hausladen, I. and Schosser, M. (2020). Towards a maturity model for big data analytics in airline network planning. *Journal of Air Transport Management*, 82: 101721. https://doi.org/10.1016/j.jairtraman.2019.101721

Himeur, Y., Elnour, M., Fadli, F., Meskin, N., Petri, I., Rezgui, Y., Bensaali, F. and Amira, A. (2022). AI-big data analytics for building automation and management systems: A survey, actual challenges and future perspectives. *Artificial Intelligence Review*, 56(10): 4929–5021. https://doi.org/10.1007/s10462-022-10286-2

Ismail, S.A., Bandi, S. and Maaz, Z.N. (2018). An appraisal into the potential application of big data in the construction industry. *International Journal of Built Environment and Sustainability*, 5(2). https://doi.org/10.11113/ijbes.v5.n2.274

Janssen, M., Brous, P., Estevez, E., Barbosa, L.S. and Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. *Government Information Quarterly*, 37(3): 101493. https://doi.org/10.1016/j.giq.2020.101493

Jia, J. (2024). An analysis of influencing factors of undergraduate scientific research ability based on grounded theory under the background of big data. *Journal of Computational Methods in Sciences and Engineering*, 24(6): 3700–3706. https://doi.org/10.1177/14727978241299183

Kamal, E.M. and Flanagan, R. (2012). Understanding absorptive capacity in Malaysian small and medium sized (SME) construction companies. *Journal of Engineering, Design and Technology*, 10(2): 180–198. https://doi.org/10.1108/17260531211241176

Kiu, M.S., Chia, F.C. and Wong, P.F. (2020). Exploring the potentials of blockchain application in construction industry: A systematic review. *International Journal of Construction Management*, 22(15): 2931–2940. https://doi.org/https://doi.org/10.1080/15623599.2020.1833436

Koseleva, N. and Ropaite, G. (2017). Big data in building energy efficiency: Understanding of big data and main challenges. *Procedia Engineering*, 172: 544–549. https://doi.org/10.1016/j.proeng.2017.02.064

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. and Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, 52(2): 21–32.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. and Byers, A. (2011). *Big Data: The Next Frontier for Innovation, Competition and Productivity*. New York: McKinsey Global Institute.

Mazzei, M.J. and Noble, D. (2017). Big data dreams: A framework for corporate strategy. *Business Horizons*, 60(3): 405–414. https://doi.org/https://doi.org/10.1016/j.bushor.2017.01.010

Meng, Q., Peng, Q., Li, Z. and Hu, X. (2022). Big data technology in construction safety management: Application status, trend and challenge. *Buildings*, 12(5): 533. https://doi.org/10.3390/buildings12050533

Mikalef, P., Pappas, I., Krogstie, J. and Pavlou, P. (2019). Big data and business analytics: A research agenda for realizing business value. *Information and Management*, 87(1). https://doi.org/10.1016/j.im.2019.103237

Miller, S. (2014). Collaborative approaches needed to close the big data skills gap. *Journal of Organisation Design*, 3(1): 26. https://doi.org/10.7146/jod.9823

Monino, J.L. (2021). Data value, big data analytics and decision-making. *Journal of the Knowledge Economy*, 12(1): 256–267. https://doi.org/10.1007/s13132-016-0396-2

Ngo, J., Hwang, B. and Zhang, C. (2020). Factor-based big data and predictive analytics capability assessment tool for the construction industry. *Automation in Construction*, 110: 1–12. https://doi.org/10.1016/j.autcon.2019.103042

Nguyen, T.L. (2018). A framework for five big V's of big data and organisational culture in firms. *IEEE International Conference on Big Data*. IEEE Xplore, 5411–5413. https://doi.org/10.1109/BigData.2018.8622377

Owolabi, H., Bilal, M., Oyedele, L., Alaka, H., Ajayi, S. and Akinadé, O. (2018). Predicting completion risk in PPP projects using big data analytics. *IEEE Transactions on Engineering Management*, 67(2): 430–453. https://doi.org/10.1109/TEM.2018.2876321

Ram, J., Afridi, N.K. and Khan, K.A. (2019). Adoption of Big Data analytics in construction: Development of a conceptual model. *Built Environment Project and Asset Management*, 9(4): 564–579. https://doi.org/10.1108/BEPAM-05-2018-0077

Regona, M., Yigitcanlar, T., Xia, B. and Li, R.Y.M. (2022). Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. *Journal of Open Innovation: Technology, Market and Complexity*, 8(1): 45. https://doi.org/10.3390/joitmc8010045

Tan, Y.J., Maaz, Z.N., Bandi, S. and Palis, P.A. (2023). Common data environment: Bridging the digital data sharing gap among construction organizations. In M.A. Al-Sharafi, M. Al-Emran, M.N. Al-Kabi and K. Shaalan (eds.), *Proceedings of the 2nd International Conference on Emerging Technologies and Intelligent Systems. ICETIS 2022. Lecture Notes in Networks and Systems*, 584: 333–342. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-031-25274-7_27

Veras, P.R., Renukappa, S. and Suresh, S. (2022). Awareness of big data concept in the Dominican Republic construction industry: An empirical study. *Construction Innovation*, 22(3): 465–486. https://doi.org/10.1108/CI-05-2021-0090

Verma, S. and Bhattacharyya, S.S. (2017). Perceived strategic value-based adoption of big data analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management*, 30(3): 354–382. https://doi.org/10.1108/JEIM-10-2015-0099

Walls, C. and Barnard, B. (2020). Success factors of big data to achieve organisational performance: Theoretical perspectives. *Expert Journal of Business and Management*, 8(1): 17–56.

Wang, H., Ye, H. and Liu, L. (2023). Constructing big data prevention and control model for public health emergencies in China: A grounded theory study. *Frontiers in Public Health*, 11: 1112547. https://doi.org/10.3389/fpubh.2023.1112547

Yang, P., Xiong, N. and Ren, J. (2020). Data security and privacy protection for cloud storage: A survey. *IEEE Access*, 131723–131740. https://doi.org/10.1109/ACCESS.2020.3009876

Yousif, O., Zakaria, R., Aminudin, E., Yahya, K., Sam, A., Singaram, L., Munikanan, V., Yahya, M., Wahi, N. and Shamsuddin, S. (2021). Review of big data integration in construction industry digitalization. *Frontiers in Built Environment*, 7: 770496. https://doi.org/10.3389/fbuil.2021.770496

Yu, T., Liang, X. and Wang, Y. (2020). Factors affecting the utilization of big data in construction projects. *Journal of Construction Engineering and Management*, 146(5): 04020032. https://doi.org/10.1061/(asce)co.1943-7862.0001807

Zhang, Y., Ren, S., Liu, Y., Sakao, T. and Huisingh, D. (2017). A framework for big data driven product lifecycle management. *Journal of Cleaner Production*, 159: 229–240. https://doi.org/10.1016/j.jclepro.2017.04.172