Building Data Driven Culture for Digital Competitiveness in Construction Industry: A Theoretical Exploration

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Despite studies related to big data in construction is growing, most of them have focused more on data application and less on the social element of the big data technology (e.g., data culture). This study aims to explore the key elements of data culture practices, towards providing a deeper insight into how they could drive digital competitiveness in the industry. A total of 136 papers related to big data in construction published in peer-reviewed journals were reviewed and analysed using the well-established systematic literature review (SLR) methodology. The findings indicate that four key drivers of data: data analytics, data literacy, data democratization and data leadership are critical for organisation's competitiveness in digital environment. A framework for data driven culture is proposed consisting of five elements: culture of production, culture of use, cultivation of data, datafication and data infrastructure. As cultural shifts are complicated endeavors, exploring the key elements on what it takes to drive the data culture in construction is necessary for the development of an effective digital ecosystem of the organisation. This study extends the digital literature in the construction context by providing deeper insights into the conceptualisation of data driven culture.

Keywords: Beliefs and behaviours, Construction and Engineering, Data-driven, Digital transformation

Introduction

Digital transformation in the construction industry is a growing trend in recent years. The pace of digital pressure is accelerating to enhance the digital stagnation in the industry. The industry is largely left behind due to lack of automation, poor planning, inefficient communication, lack of collaboration, underinvestment of R&D and these factors are hampering the productivity and project performance (Lu et al., 2015a). The recent digital technologies, including building information modeling (BIM), blockchain, big data, Internet of Things (IoT), prefabrication, 3D printing, virtual reality (VR) and robotic equipment, are starting to have an impact and gradually changing how building and infrastructure are designed, constructed, operated and maintained.

Importantly, one of the pillars of this new innovative way of working is the maximization of data usage throughout the construction project life cycle through big data technology applications. Its influence on the construction (due to the massive amount of data generated across various data-generating devices (e.g., people, computers, machines)) is impossible to ignore (Bilal et al., 2016; Alavi and Gandomi, 2017). From planning data to project performance and the supply chain related data, this big data technology is modernising the industry towards better data management practice that could improve the accuracy of project performance estimates, as well as engineering productivity. Despite the fact that big data technology offers a variety of advantages, particulary at the micro (e.g., bringing data-backed decision-making in operation) and macro level (e.g., redefine the fragmented collaboration between parties), the success of this application on the data culture of the organisation is still limited. Previous studies (e.g., Raymond and Bergeron, 2008) indicated that there is an inherent complexity in the way of project teams (across the hierarchy) collect, store and apply the data, which has led to a number of decisions that have an impact on the operations. This fragmentation can intensify the silo data culture within the construction organisations. Moreover, not having the right data culture will affect the ability of the industry to accelerate the next level of digital adoption (i.e., artificial intelligence and machine learning). Also, several challenges such as leadership neglects, team lacks digital literacy, existing fragmented culture (e.g., data management parties) and etc inhibit the cultural change towards cultivating the data-driven culture (Lu et al., 2015a).

Despite studies on data culture being well recognised and discussed in the ICT industry with regard to the humanities and social sciences (e.g., Aragona and Zindato, 2016; Anker and Clement, 2019), and information technologies (Arbury et al., 2017), progress has been limited in the construction domain. Even though there are studies related to big data in construction (e.g., Bilal et al., 2016; Alaka et al., 2018; Aghimien et al., 2021), these studies are mostly focusing more on the data applications (for example, waste management performance (Lu et al., 2015a); forecasting (Kim and Shin, 2016); behavioral modeling (Gandomi et al., 2016); predictive failure (Alaka et al., 2018) and data analytics (Aghimien et al., 2021)) than on the social aspects of the big data technology (e.g., data culture). Additionally, there is no consolidated information on the classification of the key elements embedded in data culture practice with the construction domain. Consequently, to bridge this gap in the literature, this study focuses on identifying the key elements of data culture practice and attempts to classify them, with the intention of acquire a better understanding of how they drive the digital competitiveness in the industry.

As cultural shifts are complicated endeavours, exploring key elements on what it takes to drive the data culture in construction is necessary for the development of an efficient digital ecosystem for the organisation. Aragona and Zindato (2016) emphasise that big data transformation is not totally based on technical processes but also on how social elements are incorporated to extend data visibility towards operational excellence. Organisation that embraces this data culture-driven will influence the pervasive pattern of disruption of this datacentric technology (You and Wu, 2019). Also, recognising and learning the diverse data cultures will strengthening data sharing networks across multidisciplinary organisations as well as improving the decision-making in order to ease the complex dynamics of informatization inherent in the construction projects (Naderpajouh et al., 2016). Gaining an insight into how data culture could be advanced will facilitate organisations, governments and authorities embrace the digital cultural oriented practice where digitalisation in construction is accelerating.

Research Method

This research is based on a systematic literature review (SLR) focusing on relevant past studies on data culture in construction domain. SLR approach involves a comprehensive methodology (i.e., involving the activities of searching, inclusion criteria, data extraction and synthesis) to seize works focusing on the particular context and synthesise them into numerous views relying at the study's objectives. SLR has been widely used in construction management and engineering (CME) research as a typical methodology for advancing the pattern of specific subjects; for example, risk identification and common risks (Siraj and Fayek, 2019); and design for safety (Che Ibrahim et al., 2022).

This review followed the steps of conducting a systematic literature review outlined by Osei-Kyei and Chan (2015), including three phases; 1) identification of studies; 2) selection of studies and 3) examination of the studies) to identify the key elements of successful data culture in construction organisations. The methodological framework of this study is shown in Figure 1.

Stage 1: Identification of Studies

The Scopus database was selected due to its ability to perform better than other search engines in terms of its current status, coverage and accuracy (Che Ibrahim et al., 2022). Also, Scopus has a larger coverage of unique journals in the field of construction engineering and management compared to other databases. Additionally, bibliographic records from the Scopus database can be exported directly to the selected mapping tools, facilitating the analysis process. Being the largest database, the use of Scopus also has been utilized in many recent review studies in construction domain for different purpose. As for the first step of the approach, to identify paper related data culture, the "Scopus" search engine was used to perform the search via "titles". Document type was set as "article or review" while the keywords of *data culture* (as the first search) and keywords of *data driven, data capability, data culture, data analytics, big data, data mining and construction industry* (as 2nd search) were used. By using the search strings, only 28 and 32 articles resulted from an initial search based on the title search. Considering the fact that this study analyzed data-related in construction literature, the search string was then applied to the titles, keywords and abstracts of publications in databases to capture a general view of the discourse in data-related concept, application and processes within the construction context. It also testifies the level of attention of the subject attracts in construction engineering and management (CEM) research as well as establishing broader scope of contributions. The final combination of search string is listed as follows;

TITLE-ABSTR-KEY ("data driven") or TITLE-ABSTR-KEY ("data capability") TITLE-ABSTR-KEY ("data culture") or TITLE-ABSTR-KEY ("big data") or TITLE-ABSTR-KEY ("data analytics") or TITLE-ABSTR-KEY ("data mining") and TITLE-ABSTR-KEY ("construction industry").

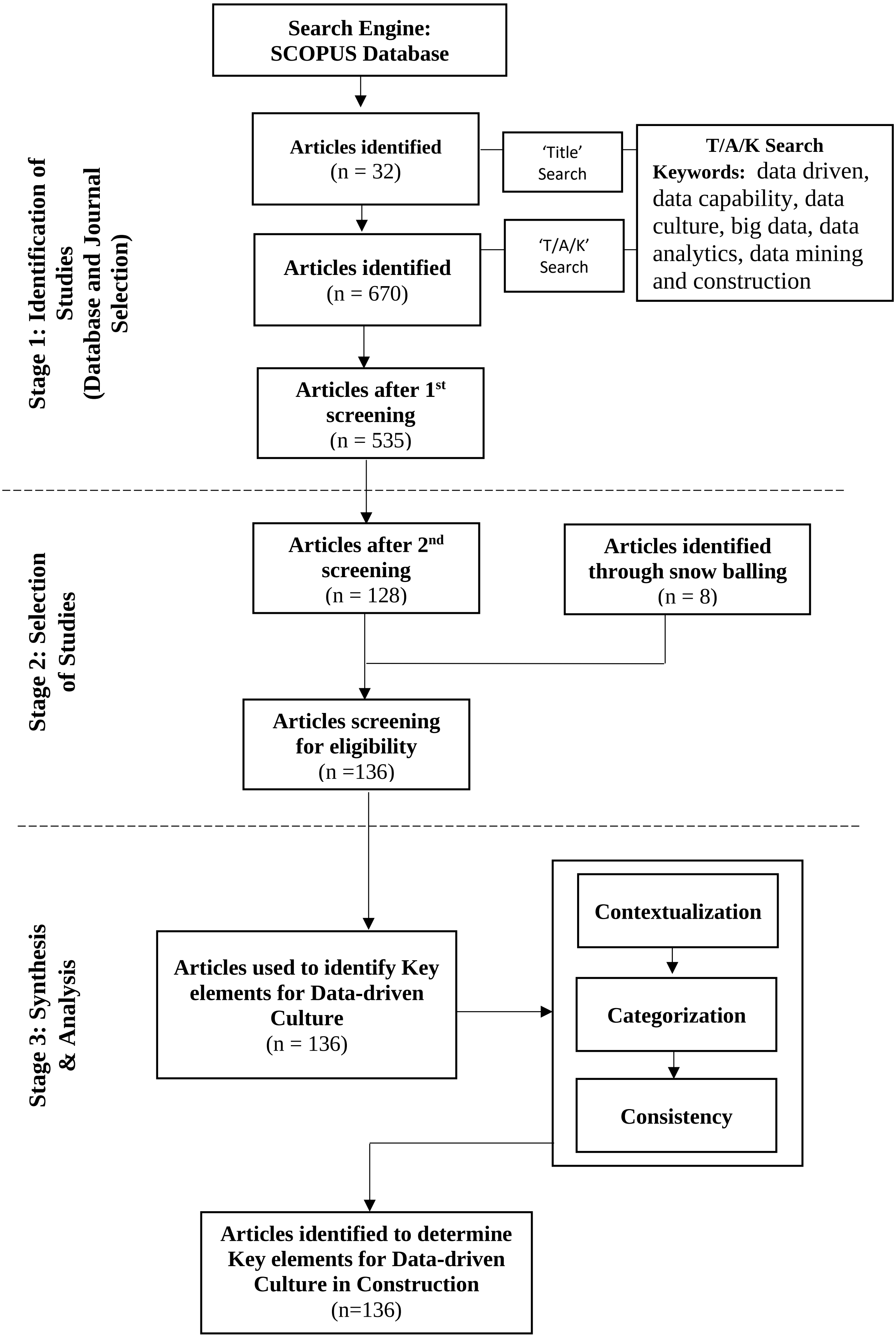

Figure 1: Research methodology for the SLR

Following the keywords input, the electronic search returned 670 articles. Also, in Stage 1, the process of screening the articles were conducted to remove irrelevant and duplication articles. The screening of the publication source was limited to journals written in English. Thus, relevant leading CME journals such as *Automation in Construction (AC), International Journal of Project Management (IJPM), Building and Environment (B&E), Journal of Construction Engineering and Management (JCEM), Journal of Computing in Civil Engineering (JCCE), Journal of Management in Engineering (JME), Journal of Building Engineering (JBE) and Journal of Civil Engineering (JCE)* were selected. As the focus of this review was on peer-reviewed articles, other types of publications were omitted from the search. As emphasised by other scholars (e.g., Jin et al., 2019), publications such as chapter in books and magazine were excluded in SLR exercise due to the lack of information provided. Borrego et al. (2014) emphasised that referring to articles that results from experimentation and systematic observation could led to high quality literature reviews. After screening out irrelevant articles and removing duplications, 535 articles remained. This searching exercise from Scopus was performed in February 2020 and it covered the until September 2022 period.

Stage 2: Selection of Studies

In Stage 2, the selection of relevant articles was performed. Acknowledging the evolving nature of Big Data in construction research, specific criteria that practical and feasible has to be set in order to ensure high quality studies (Borrego et al., 2014). Thus, the following inclusion criteria were used to select the articles: (1) the article should be specifically related to data technology-driven in the construction industry; (2) the article should focus at least on either the concept, application or process of big data in construction; and (3) the article should mention any discussion related to social aspect of data-driven activities. An overview of the inclusion and exclusion criteria are provided in Table 1. Based on this criterion, 535 articles were examined where 407 of the articles abstract failing to give a clear focus of a study, and the entire article was scrutinized. This exercise found some articles that were not relevant to construction industries research, as some articles merely focusing on environmental or economic dimensions of sustainability, where they highlighted about the adoption of data culture concepts for sustainable practices in construction industry in abstract. For example, the barriers of adopting big data related to the sustainable strategies was referred to be as an outcome of the study and the authors emphasized about the application of big data and policy drive was referred to be benefit greatly in economic, social gains and environment preservation by the adoption of it, which was not a research issue in itself.

Table 1: Specific criterion set in Stage 1 and 2 of the SLR

Stage 1: Identification of Studies		
Keywords	***Search Type***	***Results (Articles)***
"data driven" OR "data capability" OR "data culture" OR "big data" OR "data analytic" OR "data mining" AND "construction industry"	Title	32
"Data Culture"	Title	28
"data driven" OR "data capability" OR "data culture" OR "big data" OR "data analytics" OR "data mining" AND "construction industry"	Title, Abstract, Keywords	670
Initial Screening criteria	Articles written in English Peer-reviewed articles Removing any duplications / in complete articles	535
Stage 2: Selection of Studies		
Inclusion criteria	***Exclusion criteria***	***Results (Articles)***
(1) the article should be specifically related to data technology-driven in the construction industry;	(1) A lack of focus on construction project management / activities / processes and instead a focus on other	136

(2) the article should focus at least on either the concept, application or process of big data in construction; and (3) the article should mention any discussion related to practical and social aspect of data-driven activities	domain e.g., materials, electrical system, energy efficiency, etc. (2) Articles where big data / data analytics was not the core focus of the study, i.e., the concept was rarely mentioned e.g., the articles focus on statistical / mathematical model or technical aspects of specific technology.

In addition, snowballing method of identifying relevant articles that has not captured by the Scopus database has conjointly been conducted, resulting additional eight articles from journals. This in consistent with studies such as Umeokafor (2018). This exercise was carried out since the result of the first two-stage search may not provide a complete picture of comprehensive coverage of the papers that are worth reviewing. The snowballing exercise is sufficient since it allows for the inclusion of significant state-of-the-art works relevant to the study to achieve the study's objectives. Consequently, a final count of 136 articles published in 63 journals and 73 proceedings was selected (as shown in Table 2) for the content analysis for the identification of key elements to drive the data culture in construction. The inclusion of conference proceedings ensures the views of authors in developing countries are adequately capture because is their main publication outlet (Umeokafor et al. 2022).

Table 2: Distribution of articles per journal in Stage 2

Journal Type	**Journal Name**	**Frequency (Initial)**	**Frequency (Final)**
Journal (Articles & Review)	Automation in Construction	21	3
	Journal in Civil Engineering Management	3	2
	Advanced Engineering Informatics	5	1
	Journal of Construction Engineering and Management	23	4
	Journal of Management in Engineering	11	2

	Journal of Building Engineering	5	2
	Journal of Computing in Civil Engineering	5	1
	Others (examples): Building and Environment; Building Research and Information; Engineering, Construction and Architectural Management; Construction Innovation; Construction Management and Economics; Construction Economic and Building; Construction Innovation; Information Technology in Construction; Physics	204	48
Proceeding	Conference Proceedings	258	73
Total		535	136

Stage 3: Content Analysis

The Stage 3 involved the process of analysis and synthesis of the selected literature. To perform content analysis, this study used an approach proposed in previous studies (e.g., Ibrahim et al., 2013), using a qualitative content analysis, in order to identify what it takes (i.e., key elements) to drive data-driven culture in construction. Krippendorff (2013) emphasised that efforts to study on the identification of elements and examining its trends and patterns within a specific context could be done through content analysis technique. Fellows and Liu (2015) further described that any categorisation should be exclusive (i.e., where data is assigned to one category) and exhaustive (i.e., categories cover the research topic comprehensively). The categorisation in this study was developed in inductive manner, where the categories was decided after the contextualization process (i.e., identify the relevant elements). In principle, in stage 3, after the identification of the related articles, detailed content analysis was carried out based on 3 Cs (1) *Contextualization*: profile the selected articles based on its context and examine the relevant key elements of data culture in the selected articles; (2) *Categorization*: systematically categorize the key elements based their characteristics and (3) *Consistency*: the arguments among authors on the categories and key elements were compared, and discussed appropriately to reduce inherent subjectivity and potential variance.

Results and analysis

This section describes the research findings, including the descriptive analysis of the identified articles and categorization of data-driven culture identified through content analysis. The descriptive analysis (e.g., the percentage values) were determined based on the number of references over the total number of articles considered in the content analysis (i.e., 136 articles). Out of 136 articles, 46% of the articles are journal and the remaining 54% are conference papers. It is worth noting that despite the recent introduction of the concept in the industry, construction literatures have widely acknowledged that the subject of Big Data is growing significantly and receiving attention in the international prominence (perspective from different stakeholders and different context). Although there is a significant change and improvement in construction digital landscape across geographical boundaries over the recent years, the issue of understanding the data-driven organizations in digital environment remains elusive. Despite the diversity in the current thinking on Big Data, both conceptual and application, there is still a lack of effort to contextualize the Big Data in cultural context. Therefore, this study attempts to fill the gap by providing more practical views on the data-driven culture in construction organizations towards accelerating digital transformation.

Key Elements of Data-Driven Culture

Following a comprehensive content analysis, the key drivers of data culture were identified and categorized based on their nature. Importantly, the review and discussion of data culture take place in the context of the definition suggested by Acker and Clement (2019) as a phenomenon shaped by ideas about the cultivation and production of data that reflect the epistemologies of a specific field. Consequently, the key drivers of data-driven culture in this study are defined as determining factors associated with the use of cultural and support mechanisms for project teams to focus on the information conveyed by the existing data in making decisions and executing their tasks. The drivers of data culture identified from the selected articles were grouped into four main categories: (i) data analytics (i.e., descriptive analytics, prescriptive analytics, diagnostic analytics and predictive analytics), (ii) data democratization (i.e., data sharing and data governance), (iii) data literacy (i.e., information literacy; and skills and competencies) and (iv) data leadership (i.e., knowledge management and analytical leaderships). The following sections (see Table 3 for more details) briefly discuss each of these key drivers in turn about how these data cultures aid in fostering data driven culture especially in construction industry.

Data Analytics

Big Data Analytics is a booming technology that effectively handles construction projects (Marzouk and Enaba, 2019). Massive amounts of data must be gathered, organised, and analysed to find patterns and other significant information (Verma and Agrawal, 2016; Xiao et al., 2020). In order to uncover significant hidden values and draw conclusions from enormous datasets that are out of the ordinary, more complex, and on a massive scale (Tschakert et al., 2016), a combination of technologies and techniques is required that primarily focuses on addressing new or existing problems in more efficient and effective ways (Verma and Agrawal, 2016: Xiao et al., 2020).

Table 3: The key drivers of data driven culture in construction

Key Drivers	Sub Key Drivers	Definition	Implications towards data culture	Example of Authors
Data Analytics	Descriptive Analytics	Forecast future probability and patterns and provides insight into what may occur in the future.	Help through a better strategic and operational decisions, decision support, (e.g., providing recommendations) and decision automation (e.g., implementing the prescribed action) and identifying possible opportunities and potential risks and making more accurate forecasts.	Ahmed et al, (2021) and Aroujo-Rey and Sebastian, (2021); Marzouk and Enaba, (2019); Riahi and Riahi; (2018)
	Diagnostic analytics	Seek to identify the underlying potential cause of a problem		Wang et. al, (2016); Soltanpoor and Sellis, (2016); and Ngo et. al., (2020); Riahi and Riahi, (2018); Monica and Sorin, (2014)
	Prescriptive analytics	Forecasts what may occur and focused on to discover the optimum solution take which provides support for making decisions.		Banerjee, (2013); Wang (2016); Tschakert et al., (2016); Deshpande et al., (2019); and Xiao et al., (2020); Oztekin and Masterson, (2018); Delgado et. al., (2019); Bilal et al., (2016); Ngo et al. (2020)
	Predictive analytics	Forecasts the future by analysing past data and employs a variety of techniques, including data mining and artificial intelligence, to examine current data, create scenarios of what might occur, evaluating historical data, recognising trends and extrapolating correlations.		Wang, (2016); Oztekin and Masterson, (2018); and Delgado et. al., (2020); Bilal et al., (2016); Tinoco et al., (2021)

Data Democratization	Data sharing	Process of taking any type of data and making it available for other users to examine or use.	Applying data democratization in an organization requires high integrity, responsibilities and trust so that the aim of sharing data across the organization can be effectively success and transparent without data misuse and duplication of effort across different department.	Ayodele & Kajimo, (2021); You and Wu (2019) and Waithira et al., (2019); Deshwal, (2021); Ayodele and Kajimo-Shakantu, (2021); Banerjee and Kumar, (2013)
	Data governance	The collection of decision rights, processes, standards, policies and technologies required to manage, maintain and exploit information as an enterprise resource.		Janssen et al., (2020); Awasthi and George, (2020); Marijin et al., 2020 and Jessica et. al, (2021); Kim and Cho, (2018); Brous and Janssen, (2020)
Data Literacy	Information literacy	Information literacy is a set of abilities requiring individuals to recognize when information is needed and have the ability to locate, evaluate, and use effectively the needed information.	Enhance the cognitive, psychomotor and affective domain of personnel towards understanding, explore, use, make decisions with, and communicate using data.	Schield M., (2004); Forster, 2017; Wide'n et al., (2021); Seefollahi and Shahidnik, (2016); (Ahmad et. al., 2020; Wide'n et al., 2021)
	Skills and competencies	Skills that involve data/computer science, including data collection, calculation, analysis and interpretation, and communication.		Davenport and Kim, (2013); McKendrick, (2015); Matthews, 2016; Pothier and Condon (2019); Bilal et al. (2016); Chowdhury et al. (2019)
		To formulate productive questions, think computationally, think analytically, visualize and report summary data.		
Data Leadership	Knowledge management	Process which reflects strategies for acquisition and creation of knowledge, either externally or internally, sharing the preserved knowledge within the firm, and the application of knowledge.	Creating an effective communication in delivering information and data for a fast and smart decision making.	Luthra, (2015); Kuntze et al., (2016); Udin et al., (2019); Alavi and Gandomi, (2017); Fillion et al., (2015); Almatrooshi et. al., (2016); Bock and Kim, (2002)

	Leadership Communication	Inspiring and encouraging an individual or a group by systematic and meaningful sharing of information by using excellent communication skills.		Fillion et al., (2015); Almatrooshi et. al., (2016); Alavi and Gandomi, (2017); Luthra and Dahiya, (2015); Madlock (2008); Kuntze et al., (2016)

Several researchers (e.g., Oztekin and Masterson, 2018; Delgado et al., 2019) discovered that factors influencing the motivation of Big Data Analytics available within the organisation (i.e., availability of technology; technical knowledge; compatibility in operation; and availability of competent staff), the organisation's performance expectations (i.e., carry out the planned tasks, efficient task delivery, accessibility of the clients need; use of quality and valuable information on clients) and the societal influence (i.e., offers a better competitive advantage; innovativeness and the usage). The previous studies also indicated that descriptive, diagnostic, predictive, and prescriptive analytics are the common classifications for data analysis (Ngo et al., 2020).

Descriptive Analytics

Descriptive analytics is known as one of the data analytics that forecasts future probabilities and trends and offers perception into potential future events (Riahi and Riahi, 2018). The construction sector has adapted descriptive analytics to help project managers and decision-makers choose the best course of action for ongoing and upcoming projects (Ahmed et al., 2021). Marzouk et al. (2019) stated that descriptive analytics assists an organization in terms of communication nature and monitoring comparable sentiment. Descriptive analytics consist of data mining methods that offer understanding by arranging set of data to discover predicted data patterns (Riahi and Riahi, 2018). According to Ahmed et al. (2021), it is beneficial for project managers to regularly assess the project's health and to proactively enable stakeholders and decision-makers in projects make the best choices based on their effective use of business information systems and analytics. Additionally, integrating BIM and descriptive analytics has many advantages, including helping managers and project teams manage their workload in light of the many projects running simultaneously while reducing errors and avoiding misunderstandings (e.g., Marzouk and Enaba, 2019), to ensure that all projects are finished within the schedule, budget, quality, and compliance standards (Ahmed et. Al., 2021; Araújo-Rey and Sebastián, 2021).

Diagnostic Analytics

Diagnostic analytics seeks to identify the underlying potential cause of a problem (Ngo et al., 2020). Scholar Riahi and Riahi (2018), express that diagnostic analytics are beneficial to determine fundamental cause of a problem. This approach is used to determine the reasons behind occurrences and activities, and it aims to understand them (Wang et al., 2016; Riahi and Riahi, 2018). It also gives organisations the opportunity to understand the connections between various types of data (Soltanpoor and Sellis, 2016). This is because descriptive analytics able to equip an organisation the answers of why some events could happened (Riahi and Riahi, 2018). Diagnostic analytic framed a visualisation technique by using existing data to investigate the fundamental issues and cause of incidence for the events (Banerjee, 2013). According to a study by Monica and Sorin (2014), using diagnostic analytics to analyse the financial performance of the construction industry aids in predicting a high risk of bankruptcy in that industry and is very helpful in setting reference levels for diagnostic analysis of any company in the industry.

Predictive Analytics

Predictive analytics makes future predictions by examining historical data (Wang et. al, 2016; Riahi and Riahi, 2018) and uses a range of methods, such as data mining and artificial intelligence, to analyse current data, build hypothetical scenarios, assess past data, identify patterns, and extrapolate correlations (Riahi and Riahi, 2018). It can be used as a decision-support tool, for example, forecast building energy usage (González-Vidal et al., 2016). Scholar Riahi and Riahi (2018) acknowledged predictive analytics is way of forecasting upcoming event. Making the right decisions can also mean the difference between a project's success and a company's survival in a highly competitive industry like construction (i.e., the proposed approach will help stakeholders create accurate cost estimates, define correct profit margins, and decide whether or not to bid on a project) (Oztekin and Masterson, 2018; Delgado et. al., 2019). Applications for big data predictive analytics have the potential to considerably enhance project performance over the course of the project lifecycle even though they are not yet commonly used in the construction industry (Bilal et al., 2016; Ngo et al. 2020). However, predictive analytics tools have potential to cause deceptive result and processes due to dynamic changes in algorithms (Banerjee, 2013).

Prescriptive Analytics

Prescriptive analytics focused on discovering the optimum solution take (Riahi and Riahi, 2018; Deshpande et al, 2019) and provides support for decision-making for project performance improvement but is independent in drawing its own conclusions (Banerjee, 2013; Deshpande et al, 2019). Banerjee et al. (2013) explained that prescriptive analytics are utilized to idealized business model of an organisation. For instance, a large number of alternative optimization plans are created and prescribed through prescriptive analytics in the construction waste industry, allowing designers to quickly receive feedback on design modification aspects and resulting in data-driven decision-making for designing out waste (Bilal et al., 2016). In another context, Tinoco et al. (2021) emphasised that prescriptive analytics able to measure the effect of different decisions, allowing to select the best current course of action in transportation geotechnics. Banerjee et al. (2013) emphasis the prescriptive analysis guide organisation to properly figure on how solve a problem faced. These analytics allowing business model to anticipatorily encounter problem faced in decision making (Banerjee, 2013).

Data Democratization

Data democratization has been identified as one of the most important factors in fostering a data-driven culture within organisations. Due to the fragmented nature of the construction industry, the process of making digital information accessible to a wide variety of stakeholders, also known as "intra-organizational open data," is currently lacking in the world of construction companies (Bilal et al. 2016b). Such practice could improve an organization's ability to gather, process, and analyse data in order to reach critical conclusions, such as making decisions, without the influence of outside forces (Marinakis et al., 2021). Additionally, the capacity to foster data democracy could encourage a sense of shared responsibility among workers at all organisational levels (Martisoff, 2018). However, the quality and integrity of data for construction projects have been hampered due to worries about data security, intellectual property, and privacy, creating a significant barrier to the efficacy and efficiency of construction operations (Munawar et al., 2022). Huang (2021) indicated that restrictions of data sharing could cause economic losses and affect the overall benefits of construction project cost management.

However, previous studies highlight concerns on fostering the data democracy, the benefits of having such practice have resulted more innovation mechanism to enhance such practice. Previous scholars (e.g., Katal et al., 2013;) emphasise that data sharing, governance (contractual and relational) and technological advancement are fundamental requirement in embracing the culture of data democratization. Janssen et al. (2020) suggested that contractual and relational governance policies must be implemented to protect stakeholders' rights and promote data sharing. Prioritizing the creation of fair contracts with the inclusion of relational element could improve data quality, promote mutual stakeholder understanding of big data, and clearly define roles connected to big data (Janssen et al., 2020). In addition, studies (e.g., Huang, 2021) emphasised that technological innovation could facilitate in empowering the non-technical individual in making sense of the data sharing. For instance, it has been discovered that BIM technology serves as a fundamental platform for data sharing throughout the project lifetime (Azhar et al., 2012; Huang 2021). A BIM platform enables the project team to collaborate throughout the design phase, undertake reasonable analysis of the project's design scheme, and offer modification ideas, minimising any unnecessary costs and dangers during the post construction stage (Zou et al., 2016).

Data Sharing

Successful digital transformation for democratising data necessitates data sharing within the organisation in order to develop better insights and achieve the goal of value creation (Ayodele and Kajimo-Shakantu, 2021; Marinakis et al. 2021). Waithira et al. (2019) stated that data sharing activities indicates the present of departmental, institutional or data management team with data sharing policy blueprint. Data sharing facilitates the process of enquiring any type of data and making it accessible for use and examination by other users eliminating data silos and hence ensuring digital transformation within the team (Deshwal, 2021). One of the essential prerequisites for effective data sharing is assurance that the data and reported results are reliable and accurate, as well as that the rights, integrity, and confidentiality of the participants are safeguarded (Waithira et al., 2019). Data sharing is becoming more widespread in many businesses, particularly the construction industry, and for good reason: making data available benefits both individuals and society (Ayodele and Kajimo-Shakantu, 2021). Unrestricted data sharing or information exchange between clients, designers, and contractors is critical for improving collaboration, overall project performance and successful project completion (Rahman et al., 2014). Sharing data, information and resources is critical not only for ensuring successful contractual relationships (Rahman et al., 2014), but also for effective supply chain collaboration due to information being communicated efficiently and effectively (Banerjee and Kumar, 2013). One of the effective moves for data sharing management is the utilization of technological innovation associated with 4th Industrial Revolution (4thIR) that stimulate the development of data sharing and accessibility to designed data. (Ayodele and Kajimo-Shakantu, 2021).

Data Governance

Data governance can also aid in data democratization, which is the process of making wide range of data from multiple sources (e.g., the internet, mobile devices, internal networks, transaction systems, operating software, points of contact with stakeholders, and numerous other forms) available to a broad range of users within an organization. According to Jansen et al. (2020), data governance is subjecting to the action of data control by allocating the proper group of management for governing activities. The goal of broadening an organization's data user base is to make its culture more data driven and to have everyone harness the power of data. Scholars (e.g., Janssen et al., 2020; Brous and Janssen, 2020) emphasised that such culture could facilitate transparency, accountability, fairness, discrimination, and trust in the coordination and control of the use and management of data.

The implementation of data governance through clear organisational structures, responsibilities and accountability, planning and control cycles, and risks (Brous and Janssen, 2020) assists the organization in managing data silos, duplications, unclear responsibilities, and a lack of data control across its entire life cycle (Kim and Cho, 2018). Furthermore, data governance can ensure proper procedures and processes as well as secure infrastructure, resulting in individual data items being protected and managed in efficient manner (Brous and Janssen, 2020). By implementing data governance, this instrument has an all-inclusive practical effect towards performance of an organization (Janssen et al., 2020).

Data-driven Leadership

Leadership is important in developing a data-driven culture, organisational change and transformations (Davenport and Kim, 2013). The role of top management is a critical in progressing to higher stages of data-driven culture maturity in organisations (Storm and Borgman, 2020). Designing and developing organisational culture, communicating and explaining the value of data-driven decision making, securing and managing resources affects how data-driven an organisation is (Barth and Bean, 2013).

Several studies have found that leadership support is related to the development of knowledge-sharing activities among various organisations and employees (Raab et al., 2014), promotes employee mutual trust, and aids in cost reduction (Chatterjee et al., 2021). Furthermore, according to Donate and Guadamillas (2011), leadership support encourages employees to voluntarily transfer those ideas and experiences to others, aids in knowledge creation through empowerment, attempts to establish an atmosphere of belief and confidence among employees, and encourages employees to provide new ideas to develop innovation capability. Such culture would make various organisations' paths easier by transforming individuals into successful data-driven decision-makers (Carillo et al., 2019). As a result, it has been discovered that knowledge management and leadership communication are the attributes that drive data-driven leadership.

Knowledge management

Knowledge management is the meticulous process of acquiring, designing, managing, and sharing knowledge within an organisation to achieve better performance, such as the reduction of costly rework, the acceleration of work, and the implementation of best practices (Pasternack and Viscio, 1998). It plays a crucial role in aiding leaders in making smarter decisions, avoiding the need to reinvent the wheel (i.e., reducing the time and expense associated with creating knowledge from scratch), preserving some talented processes by keeping track of best practices, and stimulating innovation through knowledge and information sharing and dissemination when used appropriately (Fillion et al., 2015).

Several scholars (e.g., Alavi and Gandomi, 2017) have identified that creation, retrieval or storage, transfer, and application are the four components of the knowledge process. One of the most essential functions of knowledge management is the promotion of knowledge sharing, which is essential to knowledge creation and innovation and enables a more efficient consumption of current knowledge (Bock and Kim, 2002). Previous researchers emphasised the significance of analysing knowledge sharing and transfer (Wasko and Faraj, 2005) and the connections between knowledge management and organisational performance (Lee and Choi, 2003). Bose (2004) discovered that the relationship between knowledge management practise and organisational performance (i.e., financial, marketing, and partnership performance) is highly correlated with an organization's capacity to precisely identify the effectiveness of knowledge management in acquiring a market position. Consequently, effective knowledge utilisation results in enhanced organisational performance, particularly in data-driven leadership (Almatrooshi et. al., 2016).

Leadership Communication

Leadership communication is viewed as a complex process that begins with developing a communication strategy and continues with writing precisely and speaking effectively to manage challenging situations (Luthra and Dahiya, 2015). Several authors (Yu and Ko, 2017) found that a leader must be able to influence their employees' attitudes and provide motivation in achieving organisational goals and objectives by providing direction and exercising control, and it has been suggested that a leader's communication skills are a crucial asset for the role to operate effectively.

To be perceived as competent communicators, leaders must share and respond to information on time; listen to others' perspectives; communicate clearly and accurately to all organisational levels; and use established communication channels and various communicative resources, such as language, gestures, and sounds (Shaw, 2005). Similarly, Madlock (2008) stated that when a leader effectively communicates their perspective, they are more likely to gain the trust of their employees, which influences communication satisfaction between leaders and followers, and can simultaneously persuade employees to support their perspective by involving employee interests and communicating effectively with them.

Scholars (e.g., Udin et al., 2019) have determined that an effective communication serves multiple crucial functions. Without communication, people do not understand their roles, and the organisation cannot function effectively. Communication also plays a significant role in information sharing because it enables groups within an organisation to exchange facts, data, instructions, and guidelines (Kuntze et al., 2016). It is also necessary for message recipients to cultivate relationships and gain trust and acceptance; and enhancing their role in decision making (Udin et al., 2019).

Data Literacy

The ability to comprehend, interact with, analyse, and reason with data, known as data literacy, is a crucial factor in fostering a data-driven culture (Pothier and Condon, 2019). This set of skills is referred to as data literacy. Data literacy is required to access, manipulate, and summarise data, and data-literate individuals can work with and interpret data in a meaningful way (Schield, 2005). In addition, the data literate reader can properly evaluate information, allowing them to make critical judgments on the reliability of the presented information, as well as better understand how their own contributed data is being used and make more informed decisions when deciding what data to make available (Vahey, 2006).

The importance of data literacy is growing at all levels of society and industry, as well as in educational curricula (Koltay, 2014). Without data literacy, the data reader risks accepting biased interpretations of data as fact, leading to incorrect understanding or, worse, poor decisions, and those communicating about data who lack data literacy may inadvertently contribute to bias (Wolff et al. 2016). Thus, working with and managing data effectively saves time, money, and opportunities, but it requires data literacy throughout an organisation (Pothier and Condon, 2019).

Information literacy

Information literacy has been identified as one of the most important factors influencing data literacy to foster a data-driven culture within an organisation (Schield, 2005). Information literacy has been defined as "understanding when and how to use information to conform to organisational goals and contribute value to organisational operations" and is increasingly acknowledged as a crucial professional skill in the workplace. (Wide'n et al 2021). The ability to recognise the need for information, search for, obtain, and process it through the use of appropriate technological tools, evaluate it, and use it as effectively as possible are important characteristics of being information literate individual (Bolek et al., 2016). Additionally, proficiency in information technology, effective investigation techniques, and critical judgement and reasoning are also required to support these activities. People who have mastered the art of information literacy are equipped with the critical thinking and problem-solving skills necessary to pursue independent lifelong learning opportunities and apply their knowledge to new situations (Ranaweera, 2008).

Researchers (e.g., Seefollahi and Shahidnik, 2016) discovered that employees with a higher level of information literacy are better able to utilise the organization's social capital because they have access to information from a variety of sources, networks, and channels. In addition, information literacy is viewed as having a positive effect on social capital because it assists individuals in managing their relationships, improving the cognitive impacts towards achieving shared objectives (Ahmad et. al., 2020; Wide'n et al., 2021).

Skills and Competencies

Skills and competencies are other elements that nurture data literacy that drive the data driven culture in an organization. Due to the fact that one of the primary objectives of data literacy is to eliminate skill and knowledge gaps, specific competencies are required so that community members and organisations can use data to address local and personal issues (Matthews, 2016). Data literacy skills and competencies are not unique to data scientists, data analysis positions, or specific business intelligence jobs; rather, they are essential for employees in every department of an organisation (Pothier and Condon, 2019)

Pothier and Condon (2019) discovered that there are seven essential corporate data literacy competencies (e.g., data organisation and storage, understanding data used in a business context, evaluating the quality of data sources, interpreting data, data-driven decision making, communicating and presenting effectively with data, data ethics and security) that may contribute to the development of more data-literate individuals. Every professional must possess the knowledge and abilities necessary to work with data, and those who make decisions must be able to comprehend and apply the data they collect (Davenport and Kim, 2013). Organizations are investing in technology infrastructure to achieve their objectives, but a lack of personnel with the necessary skill sets impedes their ability to do so, which is why the workforce requires data literacy skills and competencies (Pothier and Condon, 2019). There are, however, barriers to meeting the skills and knowledge for inculcating data culture in construction. For example, financial constraints from the high cost of sourcing and/or training skills person is noted in studies such as Bilal et al. (2016b). Further, lack of organisational support, poor leadership and poor attitude towards digital technology are also reported in Chowdhury et al. (2019).

Conceptual Framework of Data Driven Culture for Digital Competitiveness in Construction Industry

The comprehensive and meticulous review resulted in the identification of specific drivers through the synthesis of 136 construction data-related papers. The four main key drivers are as follows: (1) data analytics; (2) data democratization; (3) data literacy; and (4) data leaderships. These four primary key drivers are subdivided into ten sub-key drivers.

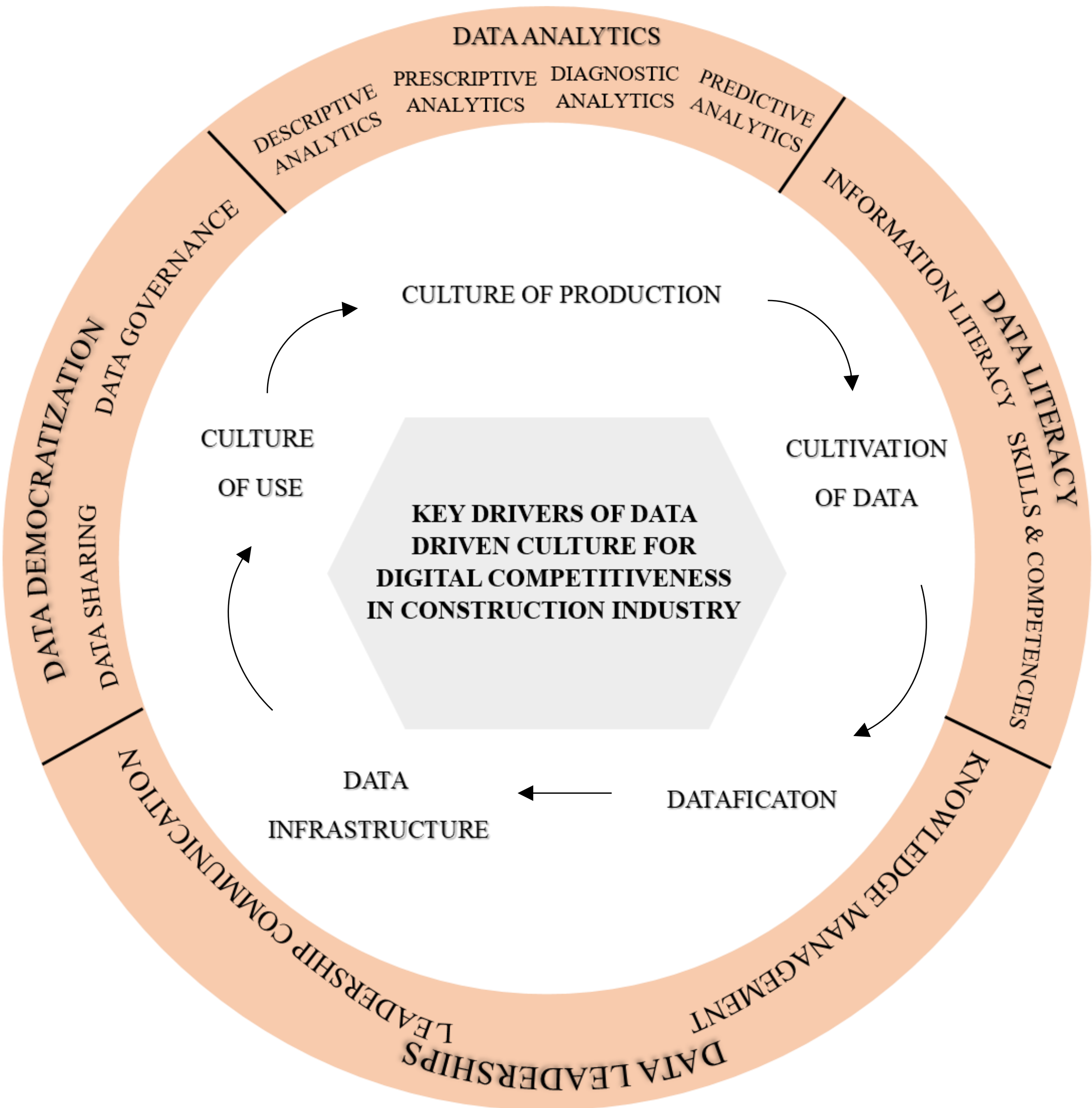

Figure 2: Conceptual Framework of Key Drivers of Data Driven Culture for Digital Competitiveness in Construction Industry

These drivers were consolidated with reference to established theories and a theoretical framework was proposed (see Figure 2) to provide an initial understanding of the data-driven culture in successful construction projects. By referring to established theory on data culture by Albury et al. (2017) and Acker and Clement (2019), it is found that the successfulness of data-driven culture is influenced by five elements: (1) cultures of production; (2) cultivation of data; (3) datafication; (4) cultures of use and (5) data infrastructures. Having such elements could provide guidance on the extent to which the data culture evolves, which then becomes a function of processes and capabilities at various organisational levels. This section will discuss the elements of data culture and the key drivers identified throughout the study in order to determine the context of their relationship.

The production of culture consists of institutionalised routines, habits, and knowledge practises within the organisation (Albury et al., 2017). To ensure that such output is established, a sense of leadership is required to ensure that continuous knowledge is stimulated and shared among teams at all levels. The continous commitment and communication of the top management is one of the most important characteristics in shaping the relationships between team that could facilitate the common organisational goals. Papadonikolaki and Aibinu (2017) discovered, for example, that leadership commitment was critical in achieving BIM adoption goals, particularly in providing continuous training and facilities; support and mentoring; and resources. Without data-driven leaders steering the ship through a digital transformation process, no organisation can or will achieve this level of operational efficiency, particularly in production; without this, the stated goal of consistently improving outcomes will not be met (Newman et al., 2016). The function in knowledge management that promotes knowledge sharing practises across organisations may also aid in the performance of data-driven leadership, which is exemplified by this production culture (Almatrooshi et al., 2016).

Cultivation of data is another perspective on data cultures. It is also known as data farming, which is defined by Horne and Meyer (2005) as a procedure established to assist decision makers in answering questions that are not addressed by traditional modelling and simulation processes. According to Albury et al. (2017), it is data that is cultivated in various ways and simply cross-pollinated a production by distributers such as corporations, governments, developers, and users. This data culture is similar to the process of collecting and organising data analytics (i.e., descriptive, diagnostic, predictive, and prescriptive analytics) generated by definition in order to discover important information (Verma and Agrawal, 2016; Xiao et al., 2020). In addition, moving towards more advanced analytics could potentially redefining the existing fragmentation (e.g., difficulty sharing data and weak interoperability of data) within the construction industry (You and Wu, 2019).

Datafication is a complex process that involves increasing the significance of data so that it influences the behaviours, values, and subjectivities present in a given environment (Bradbury, 2018). Van Dijck (2014) indicated that the use of data analytics in construction projects can improve data accessibility, and advances in data management have the potential to improve the status quo in many industries, particularly construction (Bilal et al., 2016a; Bilal et al., 2016b). As a result, the construction industry can "datafy" its operations in order to improve efficiency and revenue. This can be achieved by completing day-to-day tasks with as few resources as possible and streamlining existing processes to allow users to remain competitive. More interoperability efforts through exchanging and sharing the data across the various professionals could also be initiated to facilitate the process of datafication (Bilal et al., 2016b; You and Wu, 2019).

The term "cultures of use" refers to how users encounter, experience, exploit, and oppose data structures and processes in their daily lives, as well as how vernacular norms and practices for data ethics and safety are regulated and contested within user communities

(Albury et al., 2017). Within this culture of use, mandating the practice of data democratisation within the organisation can mitigate the challenges of data sharing without violating an individual's or organization's legal and privacy standards, thereby achieving the goal of information and data sharing. Data democratisation necessitates a team of people, technology, and procedures, all of which must be guided by well-thought-out strategy and execution plans that are well-governed in the culture of use (Bilal et al., 2016b). For instance, the idea of harnessing big data could improve the management of internal data (e.g., 2D, 3D data, financial data, corporate data, planning and schedule data, quality, safety, workforce and equipment) and external data (e.g., meteorological reports, population densities, economic and political, etc.) towards better and improved communication and coordination of construction activities with greater accuracy.

A digital infrastructure encourages data consumption and sharing while also laying the groundwork for an organisation to create, use, manage, and secure data. This solid data culture can improve the environment's efficiency and productivity, as well as cooperation and interoperability. Goldin et al. (2017) emphasised that utilising data analytic proves that the current technological advancements in cloud computing for big data processing, open new opportunities for the industry, while acting as an enabler for a significant reduction in costs and making the technology available comprehensively in the industry. Organizations in the construction industry can use connected data to detect risks, reduce costs, predict trends, reduce waste, improve forecasting, predict hazards, improve workflows, bid accurately, prevent overruns, and gain a better understanding of real-time operations (Branthone, 2021). Also, the inefficient ecosystems within the construction project (e.g., missing data, lack of automation processing the data) could also be improved through the integration with emerging trends of ICT in construction such as Building Information Modeling (BIM), virtual reality and etc. (Lu et al., 2015). Furthermore, Pothier and Condon (2019) discovered that organisations that invest in data infrastructure require data literacy skills and competencies to be successful data driven organisations.

Implication of findings

The identification of the data-driven culture framework in the current study has useful theoretical and practical implications. The research contributes theoretically to the development and exchange of knowledge regarding the drivers of a data-driven culture for construction organisations in a digitally competitive environment. Bridging the knowledge gap from typical data management in organisations to a data-driven approach in a digital environment is essential for the construction industry, particularly as digital technology applications gain momentum. From a theoretical lens, the output of the research contributes to guiding competitive strategies in organisations that help institutionalize data-related functions, processes, and capabilities at various organisational levels. In particular, it will provide guidance for various stakeholders, serving as a centralized information reference that could facilitate their data-sharing strategies within the organisation. The study is relevant to academic, industry, and policy researchers as a valuable point of reference for future research on data-related aspects in the digital environment within the construction industry in any country

In practical terms, the prioritised key drivers of a data-driven culture will serve as a guide and managerial support in decision-making, particularly concerning their ability to comprehend digital applications within their facilities or organisations. The further classification of the key elements aids managerial positions in achieving in-depth interpretations and provides continuous strategic implications for data management-related activities or processes in construction projects. The practical spectrum continues to benefit from this research, as the cultivation of a digitalization culture among construction project personnel enables the development of digital data and technology optimization. The study findings also imply that the focus on a dynamic approach to data cultivation, utilization, and infrastructure development will contribute to a holistic and effective integration of data-driven strategies within the construction industry.

Conclusion

The construction industry is experiencing a wave of digitization, generating massive amounts of data from various disciplines. This presents a significant opportunity for organizations to cultivate a data-driven culture and gain valuable strategic insights. This has resulted in four main key drivers; data analytics, data democratization, data literacy and, data leaderships with another 10 sub drivers being identified from the literature, which together form the basis for transforming a successful data-driven culture in an organisation, particularly in the construction industry. Additionally, the framework developed, encompassing the key elements of data culture, highlights the importance of production, cultivation, and utilization of data, as well as datafication and data infrastructure. By leveraging data analytics technology, democratizing data access, promoting data literacy, and having competent data leaders, organizations can achieve a culture of competitiveness and drive digitization and digital transformation.

The consolidated set of key elements of data culture derived from this paper lays a solid foundation for future developments including the creation of a maturity or assessment index for data culture practices in construction organisations. This assessment platform would enable organizations to monitor, measure, and improve their data-driven practices continuously. It could also serve as a mechanism for evaluating an organization's digital or technological capability based on relevant guidelines and best practices in the construction sector.

Additionally, piloting the framework on construction organizations would provide valuable insights for further research in this area.

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No potential conflict of interest was reported by the authors.

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Data availability statement

All data and code generated or used during the study appear in the submitted article.

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