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Data Management Practices among South African Construction Professionals: Implications for Industry 4.0 Technologies in Construction Practices

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Abstract

Purpose – This study examined the sources of construction data, the methods of data acquisition and storage, and the factors that influence data management practices among construction professionals in South Africa with a view to establishing their preparedness for Industry 4.0 technologies.

Design/Methodology/Approach - The study sampled the construction professionals registered with the South African Council for the Project and Construction Management Professions (SACPCMP). A closed-ended questionnaire was administered using an online survey tool. The data collected from a total of 134 responses were analysed using mean scores, standard deviations, one-sample t-test, and principal component analysis.

Findings – The results showed that the main sources of construction data are: firms' databases, networking with professional colleagues, and employees' personal records, with mean values of 4.19, 3.51, and 3.40 respectively. Also, findings revealed that data are stored mainly via electronic databases (*mean* = 4.33) and paper/manual records (*mean* = 3.94). The PCA result showed that project characteristics/industry/organizational idiosyncrasies and level of standardization/ICT tools/skills were the major factors influencing data management practices. While these two components have variances of 35.876% and 29.540% respectively, the two cumulatively explained 65.417% of the total variance. The study concluded that data management has become an important part of the construction professional's role

Originality/value – With the increasing integration of Industry 4.0 into construction practices, and the important roles of construction professionals in data sharing and assemblage, the paper highlights the need for conscious efforts toward ensuring good data management practices.

Keywords: Industry 4.0, data sources, construction professionals, automation, data assemblage

1. Introduction

Recent developments and advancements in automation, cyber-physical systems, digitalization, and the Internet of Things (IoT) have triggered a new phase and have redefined human interactions in businesses and exchanges. This new phase has often been referred to as the 4th Industrial Revolution (4thIR) or Industry 4.0 (Villalba-Díez *et al.,* 2020). However, despite the cross-cutting changes, extant studies (RICS Insight, 2018; Ayodele and Kajimo-Shakantu, 2021) have noted that the construction industry seems to lag in terms of the integration of automation and digitalization into its operations and practices. While studies have identified several debacles to the integration of Industry 4.0 technologies in the construction industry, Tibaut *et al.* (2016) noted that one of such major barriers is the challenge of data, in terms of its interoperability across different stakeholders' platforms. Thus, though the construction sector is data-intensive, the large amount of the data generated during the project life cycle is not adequately utilized (Sepasgozar and Davis, 2018), thereby impacting the level of adoption and integration of Industry 4.0 technologies.

A major driving force for Industry 4.0 is the increased awareness of the need to extract information from data (Ge *et al.,* 2017). Data thus becomes a significant enabler in the transition to Industry 4.0 in the construction industry. Technological tools such as virtual reality, augmented reality, drones, artificial intelligence, robotics, and simulation are gradually transforming the construction industry landscape and these tools are largely displacing traditional methods; thus, leading to an automated/digitalised system that will be largely underpinned by data. Given the increasing interest in data, there is a need for a high level of data integration across the process and operator subsystems, thereby achieving an efficient and effective human and cyber-physical relationship (Kong *et al.,* 2018). Data enables the integration and interactions of the physical and the cyber worlds (Raptis *et al.,* 2019). The foregoing suggests that data is a fundamental resource to advance the cause of Industry 4.0 in the construction industry.

The construction industry generates a large number of important data at different stages of construction projects, which include data related to cost, scheduling, productivity/quality control, safety, visualization, and building information modelling. However, given the need to ensure compatibility and interoperability across different stakeholder platforms, it is essential that construction data are stored in an accessible manner by project stakeholders (Al-Maatouk & Othman, 2018). Among other benefits, ensuring compatibility and interoperability will foster the production of knowledge and allow appropriate decision-making during the construction process.

Extant studies have noted that the ease accessing data is crucial to the success of construction projects and the integration of Industry 4.0 technologies. The assembling of construction data is a significant element in the data management process which affords its users ease of access. However, in practice, the assembling/storing, as well as the retrieval, interoperability, access, and reuse of construction data, appears difficult because the data contained in the different databases of construction firms are mainly unstructured (Yankah & Owiredu, 2016; Martínez-Rojas *et al.,* 2015). This, according to Klaubert *et al.* (2010), is because the actual data from the construction site is not always available in real-time.

The use of automated and digitalized systems has been emphasized as a way of addressing the problem of data management in the construction industry (Egbu *et al.,* 2001; Feng, 2006). However, because of the unique characteristics of the construction industry, which include: one-off projects, low level of technology awareness and training, industry fragmentation, required up-front investment, and resistance to change, the integration and adoption of automation and digitalization have not been optimally embraced in the construction industry (Betts, 1999; Feng, 2006). The ineffective use of digital technologies in the management of data/information could unnecessarily increase the volume of rework during construction projects (Al-Maatouk & Othman, 2018). Although the organising and processing (Ahmad & Nunoo, 1999), quality, and usability

(Bavafa, 2015; Ruddock, 2000) of construction data/information have been looked at in the literature, issues of data assemblage and accessibility remain a great concern among professionals in the construction industry.

Industry 4.0 is largely driven by interconnectivity and real-time data collection and processing across different systems. The data need further creates the challenge of collecting, storing, analyzing, and exploiting data in a valuable way. Poorly managed data could compromise the usability and integrity of the system and limit the integration of Industry 4.0 technologies. While existing studies have examined issues relating to information and data management systems in the construction industry, there is still a gap in the area of the nature of data management practices among construction professionals especially in the global South and the implications of this on the integration of Industry 4.0 technologies in the construction industry. Thus, to ensure an increased adoption and integration of Industry 4.0 technologies in construction practices, there is a need to examine the sources of construction data, the means of data acquisition and storage, as well as factors influencing data management practices among construction stakeholders. Hence, the study seeks to answer the following three research questions:

RQ1. What are the sources of construction data?

RQ2. What are the methods of data acquisition and storage among construction firms?

RQ3. What factors influence data management practices among construction stakeholders?

This paper is organised into five sections. Sequel to the introductory section, section two contains a review of extant studies. Section three provides the research method adopted for the paper. The discussions of findings are presented in section four and the fifth section contains the conclusions.

2. Literature Review

2.1 Construction Data Forms and Sources

The general reluctance of the construction industry to adopt automated and innovative technologies when compared to other industries, such as manufacturing, could be partly triggered by the poor data management practices being employed and stakeholders' apathy towards sharing compatible data across different stakeholders' platforms. While the gains of digitalization and in a broader sense, Industry 4.0 are numerous, the underpinning issue surrounding construction data accessibility sources and forms needs to be given careful consideration (Akinosho *et al.,* 2020)

The construction process involves a vast amount of data which could be in the form of numeric, textual, graphic, multimedia, and other construction information. These are assembled from various sources, which include sensors, experiments, meters, and websites (Bilal *et al.,* 2016). Broadly speaking, construction data can be accessed from two sources: internal and external (Corey *et al.,* 1998; Royal Institution of Chartered Surveyors [RICS], 2019).

In their study on data warehousing, Corey *et al.* (1998) categorised construction data sources into operational sources, which include accounting payroll, company and project finance, cost estimates, material inventory and equipment, and external sources such as a list of income and demographic information. In the same vein, RICS (2019) categorized the data sources into internal sources, which are property-specific; and external sources, which comprise data on other properties not owned by a particular client. These include financial, economic, socio-economic, political, technical, etc. which inform strategic decision-making.

Internal data are available on the database of firms. On the other hand, external data can be accessed from the database of other firms. These data sources include the database of public institutions, networking with professional colleagues, professional institutions (such as The Association of Schools of Construction of Southern Africa; ASOCSA), clients' databases, print/mass media, construction journals and publications, and government databases (e.g. Statistics South Africa; StatsSA and South African Reserve Bank; SARB). With the advent of the internet, external data is now more readily available than in the past, though it may cost some amount to access some of these databases.

The increasing use of the Internet has led to a large volume of data generated from social media platforms, which could potentially yield valuable business data (Boyd, 2015). Today, social media has become an important tool for improved communication and collaboration among employees in various industries (Azhar *et al.,* 2019) and the construction industry is not left behind. Extant studies have identified emerging trends such as the application of social media data to issues of stakeholder management, health and safety among others.

Data sourcing among construction stakeholders is often expensive, and the traditional methods of data collection are often time-consuming and costly (Tang *et al.,* 2015). The adoption of social media affords the opportunity of overcoming a number of these challenges and extract information in a timely and inexpensive manner (Tang *et al.,* 2017). However, despite these benefits, the use of social media as a source of data within construction organisations has not been optimally employed, perhaps due to some challenges. Azhar *et al.* (2019) noted that some attendant risks and challenges could make construction firms hesitant when considering its implementation.

2.2 Methods of Data Acquisition and Storage

A critical component underpinning the decision support system is the acquisition of accurate and reliable data and the importance of this comes to the fore in decisions relating to the construction process. The acquisition of construction data on and off-site could be through manual or digital methods. The manual method involves the recording and analyzing of data in paper documents. This process takes 30 to 50 per cent of the field supervisory personnel's time (McCullouch, 1997) and the data are not always accurate, recent, and adequate (Taneja *et al.,* 2010). Traditional methods of data acquisition employed in the construction sector often pose various problems. The desire for accurate and updated information has seen the emergence of digital technologies which are recently being adopted at different construction phases. Compared to manual methods, digital technology methods have great potential to prevent cost and time overruns and improve project communication among stakeholders. Thus, with increasing technological innovations, the deployment of electronic data acquisition technologies and wireless technologies has been on the rise in the construction sector (Chen *et al.,* 2022).

Existing studies such as (Oesterreich and Teuteberg, 2016) noted that the performance of the construction industry is significantly hampered by the crude method of transmitting the information. Davila-Delgado *et al.* (2020) stated that the construction industry is fragmented, data-intensive, and project-based, with large amounts of data exchanges and processing requirements during the project's life cycle. The increasing use of the Internet had led to the emergence of big data. These big data could often assist in generating valuable information (Tang *et al.,* 2017). However, given the large size of these data sets and the challenges of storing the vast amount of data, collaboration and seamless communication can be achieved through the use of information control systems, such as cloud computing (Oke *et al.,* 2021).,

Available studies on the methods of data acquisition have focused extensively on the tracking of progress, damage detection and safety management, and the location of human and material resources within and outside construction sites. Broadly, the technologies that are relevant in the acquisition of data are classified into four, namely: geospatial technologies (barcoding, ultra-wideband *UWB*, radio frequency identification *RFID*, global positioning system or geographic information system *GPS/GIS*); 3D imaging technologies (photo/videogrammetry, range images, and 3D laser scanning); enhanced IT technologies (e.g., e-mail, multimedia tools, voice-based tools, and handheld computing); and augmented reality (El-Omari & Moselhi, 2009; Omar & Nehdi, 2016). In the category of geospatial technologies, the RFID permits the use of tags and a reader which sends radio frequency signals to read data. This technology, according to Song *et al.* (2006) is becoming popular for long-range tracking of the delivery of high-value materials on construction sites. However, poor communication frequency can be an obstacle to long-range tracking in large construction sites (Jog *et al.,* 2011).

The collection of construction data has also been enhanced by the use of digital technologies, which include email, handheld computing, voice-based tools, and multimedia tools. Email is considered to be a highly effective method for tracking, storing, and extracting progress data (Elamin *et al.*, 2009; Hegazy & Abdel-Monem, 2012). Handheld computers and tablets such as smartphones and personal digital assistants (PDAs) (Ghanem, 2007; Tserng *et al.,* 2005) are also used in the construction industry. To record and update site material logs in construction projects, Sunkpho *et al.* (2000) and Tsai *et al.* (2007) utilised voice recognition with the aid of handheld devices. Hegazy *et al.* (2008) noted that the importance of multimedia tools lies in their ability to enable visualization and highlighting of problem areas. Delgado *et al.* (2020) noted that factors limiting the adoption of augmented and virtual reality among construction firms concern the lack of standards for data exchange and issues of data security and ownership

2.3 Factors Influencing Efficient Data Management Practices

Given the increased level of technological development, typified by sensors, network communication, wireless transmission, smart mobile devices and cloud computing, an enormous volume of data is collected across different platforms in increasingly complex structures and forms

(Koseleva and Ropaite, 2017). This necessitates the need for efficient data management practices (Koseleva and Ropaite, 2017). Ayodele and Kajimo-Shakantu (2020) submitted that construction data is often not optimally used due to poor data management practices which manifest through poor and unstandardized methods of data collection. Poor data management practices often impede the use to which data can be put and the level of interoperability/compatibility across different stakeholder platforms. Osunsami *et al.* (2020) highlighted the high cost of data protection and data security as major factors impacting automation and digitalization among construction firms. Akinosho *et al.* (2020) identified data availability, ethics, data privacy and protection as some of the challenges to digitalization in the construction industry. Thus, while digital and automated systems best work with the availability of large data, it appears that stakeholders are still significantly worried about issues of data privacy. Prabhakaran *et al.* (2022) noted the issue of interoperability as one of the challenges confronting the construction industry and impacting the adoption and integration of Industry 4.0 technologies. Interoperability as noted by the authors relates to the ability of the modelling tools to exchange data without undergoing multiple iterations. The need for efficient data management stems from poor data management practices which have been noted as a significant debacle to the increased uptake of Industry 4.0 technology by stakeholders in the construction industry.

Betts (1999) submitted that factors influencing data management practices among construction stakeholders include fragmentation of the construction industry, level of technology awareness, training, and resistance to change. Other factors identified by Barthorpe *et al.* (2003) include the uniqueness of each project, the complexity of the construction process, and industry/firms' practices.

Bilal *et al.* (2016) identified some challenges to the application of big data in the construction industry, one of which is the issue of data quality and the cost implication of acquiring data. Thus, given the large volume of construction data generated and exchanged during the project life cycle, an efficient data management practice becomes an important subject, as the technological advances and innovation being experienced in the construction industry are being propelled on the wheels of efficient data management and sharing among project stakeholders. Efficient data management practices are a prelude to efficient data sharing by stakeholders in the industry. Hence, where data management practices are inefficient and loosely managed, the goal of ensuring increased data-sharing practices among construction stakeholders becomes a mirage. Poor data management practices will hamper the level of data interoperability across different stakeholders' platforms, and lead to increased cost of data assemblage. These will consequently impact the seamless integration of Industry 4.0 technologies. Ayodele and Kajimo-Shakantu (2021) noted that inefficient data management practices, especially in the manner of data production and storage over the life of the project, could significantly impact data-sharing practices among project stakeholders.

The summary of the foregoing showed that data exchanges are central to activities in the construction industry. While extant studies have alluded to poor data-sharing practices among construction firms, it might be expected that most construction firms will prefer data-sharing using electronic data sources. Existing studies suggest that there has been documentation of data sources and data management practices, there has however been a dearth of evidence from the global South. The South African construction industry is a significant industry on the African continent, thus an examination of data management practices among South African construction professionals becomes germane.

3. Research Method

The study adopted a quantitative research approach, and the target population is construction professionals in South Africa. To achieve national coverage, the closed-ended questionnaire was administered via an online survey tool. Before administering the survey, the questionnaire was pre-tested with two practising construction professionals. While one of the practitioners is both a consultant and an academic with over 5 years of teaching experience, the second is a practising quantity surveyor with over 8 years of professional practice. The suggestions and comments as noted by the practitioners on the initial drafts related to the choice of words and the need for the inclusion of some variables. These comments were duly integrated into the final version of the questionnaire. Having sought and obtained the institutional ethical clearance for the conduct of the survey, the South African Council for the Project and Construction Management Professions (SACPCMP) assisted in sending the survey link via emails to construction professionals on the SACPCMP database. Further follow-up correspondence was done personally through referrals. The survey was administered from March to August 2020. Out of a total of 2,062 professionals reached via emails, only 134 responses were duly filled and found suitable for analysis. This represents 6.50% of the total sample. While studies such as Daikeler *et al.* (2020) have noted that web-based surveys yield lower responses; about 11% lower, when compared to other survey modes, the low response rate could also have been further influenced by the respondents' apathy owing to the aftermath of the COVID-19 pandemic. However, despite these drawbacks, the survey responses could still serve as a representation of the perspectives of construction professionals in South Africa given the size of the participants (134).

In analyzing the respondents' and firms' profiles, the study employed the use of frequency counts and percentages. Regarding the sources of construction data (second section), the respondents were required to rate the frequency of usage of each data source on a 5-point Likert scale ranging from 1 - Never to 5 - Always. The data sources were extracted from the study of Windapo and Qongqo (2011) and modified based on interactions and comments received during the pre-test survey. Issues on data management practices (third section) were examined under three subsections. These are the methods adopted in storing data, the frequency of data updates, and the use of data management systems. These required the respondents to rate the items on a 5-point scale ranging from 1 - Never to 5 - Always. The questions on the factors influencing data management practices were contained in the fourth section. Presented in Table 1 are the factors influencing data management practice as extracted from the literature. These were rated based on the respondent's level of agreement, that is; 1- Strongly Disagree to 5 - Strongly Agree.

The mean scores, standard deviations, and one-sample t-test were analysed for each of the components in the second and third sections. The use of parametric statistical tests is based on the assumption of normality of the data sets being employed. Given that the respondents' ratings are based on a 5-point Likert scale, in the analysis of the one-sample t-test, a test value of 3.0 was adopted. This was determined using the mid-point of the 5-point scale, i.e., (1+2+3+4+5)/5 = 3.00. Hence, mean scores below the test value were regarded as not significant. This approach has been employed by previous studies such as Ayodele and Kajimo-Shakantu (2021). The internal consistency of the factors influencing data management practices was analyzed using the Cronbach alpha test. The result gave an alpha value of 0.902. Given that the alpha value is greater than 0.700, the result shows that the items have an acceptable measure of reliability and consistency (DeVellis, 2012).

Subsequently, the study employed exploratory principal component analysis (PCA) in grouping the factors. The PCA was employed to summarize the data into a few groups representing a combination of original variables so that underlying relationships and patterns can be interpreted and understood. The PCA analysis employed the Varimax rotation method with Kaiser normalisation in grouping the factors into components/clusters of the original variable. For each factor and component, the study also analysed the mean scores and standard deviations.

Table 1. Factors Influencing Data Management Practice

Factors	Sources
Level of complexity of each project	Barthorpe *et al.* (2003)
Relative uniqueness of each project	Barthorpe *et al.* (2003)
Number of project stakeholders	RICS Insight (2018)
Fragmented Nature of the Construction Industry	Betts (1999)
Organizational culture and practices	Betts (1999); Barthorpe *et al.* (2003); Che-Ibrahim *et al.* (2019)
Level of coordination among project stakeholders	Pamulu (2004)
Means of communication among project stakeholders	RICS Insight (2019)
Project lifecycle	Sarkar and Thakkar (2018); Al-Maatouk and Othman (2018)
Level of standardization in documents and data	Ruddock (2000); Ahuja (2009); RICS Insight (2019)
Availability of required software	Pamulu (2004)
Level of ICT knowledge and skills	Betts (1999); RICS Insight (2018)

4. Findings and Discussion

4.1 Profile of the Respondents

As presented in Table 2, an examination of the respondents' roles in the construction firms showed that the majority (38.10%) were construction/project managers. Also, 21.6% were Quantity Surveyors, 10.4% and 11.2% were Engineers and Builders respectively. Architects and Estate/Facility managers accounted for 3.7% and 8.2% respectively. The responses regarding the academic qualifications of the respondents showed that 49.3% had Honours, while 20.9% and 6.0% had Master's and PhD degrees respectively, and a total of 11.2% had Matric. The years of experience of the respondents in the construction industry revealed that while 42.5% have had above 20 years of working experience in the construction industry, only 11.9% have spent 5 years and below. A total of 17.9% and 17.2% have had 6 to 10 years and 11 to 15 years of work experience respectively. The responses about the respondents' cadre showed that 14.9% were low-level employees, 25.4% and 19.4% were mid and senior-level employees respectively. A total of 40.3% of the respondents were firm executives.

Analysis in Table 2 further showed that the firm's size ranged from a small firm (23.9%) to micro and medium-sized, these accounted for 10.4% and 38.8% respectively. Large and multinational firms accounted for 19.4% and 6.7% respectively. The years of organizational establishment showed that 67.2% of the firms have been in existence for over 15 years, and only 9.7% of the firms were established 5 years below. A total of 14.9% and 8.2% of the firms were established between 6 to 10 years and 11 to 15 years respectively.

The foregoing suggests that the respondents were from across a variety of built environment professions and have had significant years of experience in the construction industry. Also, given the academic background and management cadre of the respondents, it is expected that they would give well-suited responses to issues of data management practices in the firms and the construction industry at large. The profile of the firms also suggests that most of the firms have been in existence for over 6 years cutting across small, micro, and multinational construction firms.

Table 2. Respondents and Firms' Demographics

Profiles		Frequency	Percentage
Respondents Role	Architect	5	3.7
	Builder	15	11.2
	Engineer	14	10.4
	Construction/Project Manager	51	38.1
	Quantity Surveyor	29	21.6
	Estate/Facility Manager	11	8.2
	Others	8	6.0
	No Response	1	0.7
	Total	*134*	*100.0*
Academic Qualifications	Matric	15	11.2
	Honours	66	49.3
	MSc	28	20.9
	PhD	8	6.0
	Others	17	12.7
	Total	*134*	*100.0*
Years of experience in the Construction Industry	5 years and below	16	11.9
	6 to 10 years	24	17.9
	11 to 15 years	23	17.2
	16 to 20 years	10	7.5
	above 20 years	57	42.5
	No Response	4	3.0
	Total	*134*	*100.0*
Management cadre	Lower Level	20	14.9
	Middle Level	34	25.4
	Senior Level	26	19.4
	Executive	54	40.3
	Total	*134*	*100.0*
Firms Profile			
Size of firm	Small Firm	32	23.9
	Micro	14	10.4
	Medium Sized	52	38.8
	Large	26	19.4
	Multinational	9	6.7
	No Response	1	0.7
	Total	*134*	*100.0*

Years of organizations' existence	5 years and below	13	9.7
	6 to 10 years	20	14.9
	11 to 15 years	11	8.2
	above 15 years	90	67.2
	Total	*134*	*100.0*

4.2 Sources of Construction Data

The results of the sources of construction data as presented in Table 3 show that the major sources of construction data are firms' databases and networking with professional colleagues and employees' personal records. These have mean values of 4.19, 3.51, and 3.40 respectively. They are also statistically significant at $p < 0.000$. The least rated sources of construction data by the firms include print and mass media (*mean* = 2.92; $p = 0.477$), and other firms' databases (*mean* = 2.57; $p = 0.000$). These have negative mean differences of -0.08 and -0.43 respectively. Other sources with statistically significant mean values at $p < 0.05$ are government databases (*mean* = 3.27; $p = 0.018$) and databases of public institutions (*mean* = 3.26; $p = 0.005$). The result suggests that while firms rely significantly on their databases, professional networking among professional colleagues still serves as a major source of obtaining construction data by the construction firms.

A major finding from the result also suggests that there is less collaboration among construction firms regarding data sharing, as this was rated the least among the sources of construction data. The firms thus rely more on internal data sources as opposed to external data sources. This affirms the *a-priori* expectation that firms will make more use of internal data sources as opposed to external sources from other construction firms.

Table 3. Sources of Construction Data

	Descriptive Analysis		**One-Sample Test (Test Value = 3.0)**		
Sources of Construction Data	**Mean**	**Std. Dev.**	**t**	***p*-value**	**Mean Diff.**
Construction firm's database	4.19	1.056	13.006	0.000	1.19
Networking with professional colleagues	3.51	1.026	5.708	0.000	0.51
Employees personal records	3.40	1.114	4.125	0.000	0.40
Government databases	3.27	1.298	2.406	0.018	0.27
Database of public institutions	3.26	1.065	2.849	0.005	0.26
Clients' personal records	3.13	1.151	1.281	0.202	0.13
Construction journals and publications	3.05	1.134	0.459	0.647	0.05
Professional Institutions	3.00	1.236	0.000	1.000	0.00
Print/Mass media	2.92	1.216	-0.713	0.477	-0.08
Other firms' database	2.57	1.110	-4.454	0.000	-0.43

4.3 Analysis of Data Management Practices

The study examined the data management practices of construction firms. This was assessed under three sub-sections, the first examined the methods adopted by the firms in storing construction data, the second and third assessed the frequency of construction data update by the firms, and the use of data management systems by the construction firms respectively.

An examination of the method of data storage by the firms as presented in Table 4 showed that the firm's electronic database (*mean* = 4.33) was more highly rated than other means of data storage. The least rated mediums of data storage are public databases (*mean* = 3.24), and employees' manual records (*mean* = 3.19). These results were further analysed for statistical significance using the one-sample t-test at a test value of 3.00. The result showed that the statistically significant responses are firms' electronic database ($p = 0.000$), firms' manual records ($p = 0.000$), employees' electronic database ($p = 0.000$), and public database ($p = 0.048$). Employees' manual records were not statistically significant. This had a p-value of 0.088.

Analysis of the frequency in which the construction data were updated showed that the most adopted means of the update was project-based. This had a mean value of 4.19, significant at $p < 0.05$. Time-based updates had a mean value of 3.20 and a non-significant p-value of 0.102. The update of data based on projects might be influenced by the frequency of project completion. Hence, construction firms rely largely on in-house construction data, generated from their own projects to update their database.

The responses on the use of data management systems showed that data management systems were largely used by construction firms. This had a mean score of 3.57, a positive mean difference of 0.575, and a significant p-value of 0.000. The result suggests that where management systems are employed by the firms, the ease of data sharing could be ensured and the challenges of interoperability and compatibility are gradually surmounted.

Summarily, the results show that electronic data storage was mostly adopted. Specifically, one of the proven benefits of using electronic storage, especially the cloud, is the safety of the file even when the hardware components are damaged. Past studies which include Tserng *et al.* (2005), Ghanem (2007), Elamin *et al.* (2009), and Hegazy and Abdel-Monem (2012) have also revealed that electronic storage such as email and handheld computers are increasingly embraced by construction firms. The frequency of the construction data based on the available projects is an indication of the peculiarities that make one project different from the other. Contrary to Ayodele and Kajimo-Shakantu's (2020) submission that construction data is often not optimally used due to poor data management practices, the result showed that firms employ data management systems in the storage and retrieval of construction data. There seems to be an increased level of data sharing among construction professionals in the construction industry due probably to the COVID-19 pandemic. Based on Ahuja's (2009) submission that construction data are still exchanged via conventional human interactions and hard copy documents, the level of satisfaction with the data sharing could be a case for further investigation.

Table 4. Data Management Practices

	Descriptive Analysis		**One-Sample Test (Test Value = 3.0)**		
Data Management Practices	**Mean**	**Std. Dev.**	**t**	***p*-value**	**Mean Diff.**
Method adopted in Storing Construction Data					
Firm's electronic database	4.33	0.927	16.556	.000	1.331
Firm' paper/manual records	3.94	1.047	10.311	.000	0.939
Employees electronic records	3.82	1.248	7.519	.000	0.823
Public database	3.24	1.358	1.995	.048	0.237
Employees manual records	3.19	1.276	1.718	.088	0.192

Frequency of Construction Data Update					
Project-based	4.19	1.009	13.514	.000	1.191
Time-based	3.20	1.372	1.649	.102	0.205
Use of Data Management Systems					
Use of data management systems	3.57	0.992	6.709	.000	0.575

4.4 Factors Influencing Data Management Practices

Having examined the data management practices, the study analysed the factors influencing data management practices among construction firms, using principal component analysis (PCA). The preliminary analysis, examining the factorability of the constructs based on the KMO and Bartlett's test of sphericity gave a KMO value of 0.847, significant at *p* = 0.000. This shows that the data set is adequate and satisfies the criteria for factorability.

Having met the condition for factorability, a two-factor solution was arrived at given the examination of the scree plot (Figure 1) and also the interpretability of the factor loadings under each component. The outputs, as presented in Table 5 (total variance explained table), show that the items converge under two components. These two components represent 65.417 of the percentage cumulative variance. While the first component accounted for 35.867%, the second component accounted for 29.540 of the total variance.

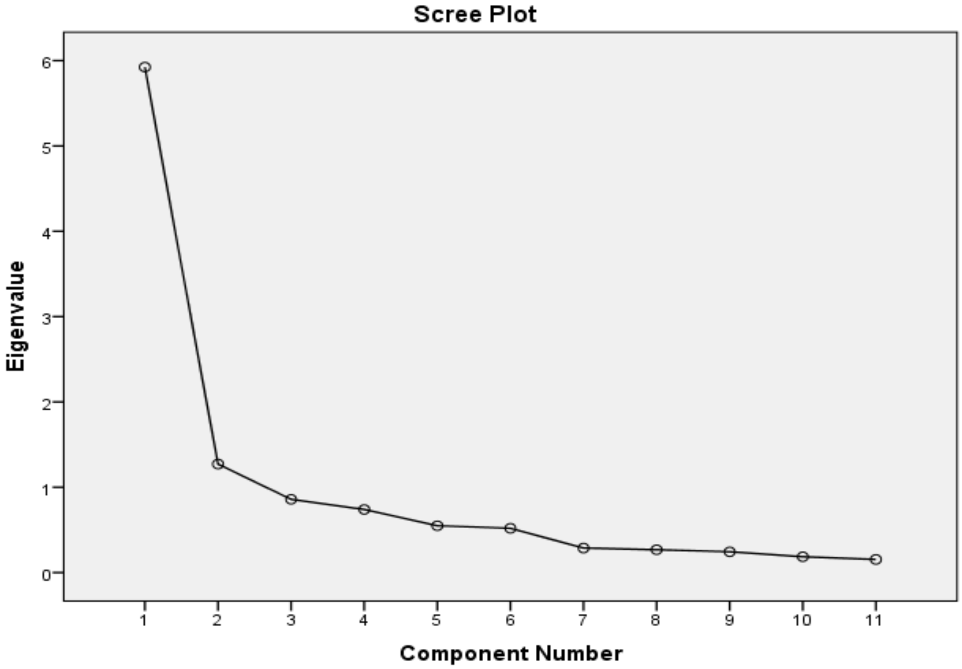

Figure 1. Scree Plot of factor extraction

Table 5. Total Variance Explained Table

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.924	53.855	53.855	5.924	53.855	53.855	3.946	35.876	35.876
2	1.272	11.562	65.417	1.272	11.562	65.417	3.249	29.540	65.417
3	.858	7.804	73.220						
4	.740	6.723	79.944						

Extraction Method: Principal Component Analysis

Table 6 (rotated component matrix) presents the factor loadings, extraction, Cronbach alpha, and the mean and standard deviation values of the factors. The first component is termed Project Characteristics and Industry/Organizational Idiosyncrasies, while the second component is termed Level of Standardization and ICT Tools/Skills. An examination of the first component showed that factors loaded under it are the level of complexity of each project, relative uniqueness of each project, number of project stakeholders, fragmented nature of the construction industry, organizational culture and practices, level of coordination among project stakeholders, means of communication among project stakeholders, project lifecycle.

Extant studies such as Che-Ibrahim *et al.* (2019) and Ahmed *et al.* (2018) have highlighted that one of the major factors influencing the level of data sharing is organisational culture and practices. Most often multinationals and large construction companies usually are reluctant towards data sharing, as opposed to smaller construction companies. This owes to the access to data enjoyed by large companies. Hence, efforts at ensuring data-sharing practices may not be encouraged by larger firms given their access to data and perceived market dominance. Based on the level of complexity and the uniqueness of construction projects, firms form a short-term contractual alliance, which is terminated upon completion of the project. Depending on the number of project stakeholders and the nature of the contractual term, this could pose a challenge to data sharing, due to the project participants' inability to share and keep project data, such data could be lost (Zhang and Fai-Ng, 2012). Also, gathering data in an ad hoc manner, different means of recording, availability of data management tools, lack of clearly defined roles for the project participants and varying levels of experiences by project participants, could pose a barrier to data sharing an assemblage among construction firms (Von-Tran and Kanjanabootra, 2013).

Factors loaded under the second component are the level of standardization in documents and data, availability of required software, and level of ICT knowledge and skills. Though a large volume of data is generated during projects, however, the inconsistent means through which the data is produced and shared often lead to issues of interoperability. This brings to the fore the challenge of data interoperability and the level of ICT knowledge and skills. Data collated during construction projects are often incompatible with other databases, owing to the lack of standardized methods of data assemblage. Incompatible and interoperable data sets undermine the usefulness of data among construction firms.

Nassar (2007) noted that the lack of data standardization and the unstructured mode of data storage pose significant challenges to data sharing in the construction industry. Lack of standardization is often a result of the fragmented and silo operations for which the construction industry is known. The challenge of unstructured data, the unstandardized method of data gathering, other issues of interoperability and the bias by construction firms towards data will adversely impact the level to which digital and innovative technologies can be integrated into construction activities.

Table 6. Rotated Component Matrix

Components/Factors	Factor Loadings	Extraction	Cronbach Alpha	Mean	Std. Dev.
1. Project Characteristics and Industry/Organizational Idiosyncrasies					
Level of complexity of each project	.882	.780	0.888	3.87	0.979
Relative uniqueness of each project	.855	.751		3.81	0.901
Number of project stakeholders	.703	.681		3.70	1.072
Fragmented Nature of the Construction Industry	.674	.561		3.66	1.018
Organizational culture and practices	.669	.685		3.73	1.043
Level of coordination among project stakeholders	.618	.555		3.60	1.051
Means of communication among project stakeholders	.566	.633		3.70	1.060
Project lifecycle	.444	.346		3.62	1.096
Component Aggregate Mean				*3.71*	*0.798*
2. Level of Standardization and ICT Tools/Skills					
Level of standardization in documents and data	.870	.788	0.841	4.03	0.974
Availability of required software	.850	.789		3.68	1.127
Level of ICT knowledge and skills	.761	.626		3.68	0.991
Component Aggregate Mean				*3.79*	*0.898*

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

An examination of the reliability of the two components using the Cronbach alpha test showed that the first, with 8 factors, had an alpha value of 0.888, while the second component, with 3 factors, had a Cronbach alpha value of 0.841. These Cronbach alpha values suggest a good measure of internal consistency and reliability among the constructs making up the two components. An examination of the mean scores of each component shows that the first component had an aggregated mean score of 3.71, while the second component had an average mean score of 3.79. An item-by-item analysis of the factors under each component showed that concerning items under the first component, the level of project complexity (*mean* = 3.87) and relative uniqueness of each project (*mean* = 3.81) were factors having the highest mean values. Items with the least mean scores are the level of coordination among project stakeholders and the project lifecycle. These had mean values of 3.60 and 3.62 respectively. Regarding the second component, the Level of standardization in documents and data had the highest mean score of 4.03. This is followed by the level of ICT knowledge and skills (*mean* = 3.68) and availability of required software (*mean* = 3.68).

An examination of the standard deviation values suggests that the first component, Project Characteristics and Industry/Organizational Idiosyncrasies, had a lower standard deviation value of 0.798, compared with 0.898 for the second component: Level of Standardization and ICT Tools/Skills. This suggests that there is a lower level of divergence by the respondents in terms of the influence of Project Characteristics and Industry/Organizational Idiosyncrasies on data sharing among construction stakeholders.

The influence of project characteristics and organizational culture on data assemblage and management corroborates extant studies such as *Barthorpe et al.* (2003) and Betts (1999). These findings underscore the need for organizational culture and industry practices that encourage efficient data management systems that will engender seamless data-sharing practices among construction stakeholders. In addition, studies such as Ahuja (2009) and Ayodele and Kajimo-Shakantu (2020) have highlighted the implications of data standardization and the use of digital tools in enhancing data-sharing practices. Where vast amounts of unstructured data are generated during the construction process and stored manually, the goal of data standardization and assemblage becomes a mirage, thereby making data sharing among different stakeholder platforms a difficult task.

5. Conclusion

The findings of this study have implications for construction stakeholders. For the construction industry to fully benefit from the gains of Industry 4.0, construction firms must begin to embrace efficient data sharing and assemblage practices. The study also concludes on the need to re-orientate construction professionals with respect to timely and accurate data as well as sharing of the same across compatible platforms. The increased synergy between firms and other construction stakeholders concerning data sharing and assemblage should also be encouraged. The findings from the study can serve as a basis to stimulate stakeholders to cut back on silo thinking and fragmentation and encourage data sharing and assemblage. This will enhance the productivity of the construction industry and encourage seamless and optimal integration of Industry 4.0 technologies in the construction practice.

The paper implies that data management is becoming an important part of the construction professional’s role and as such, conscious efforts must be geared toward ensuring good data management practices. Some initiatives that could enhance increased data-sharing practices among construction firms include: building up appropriate internal competencies to mitigate the challenge of knowledge and required skills; enlightenment of construction stakeholders about the benefits of data sharing and the centrality of data to the increased uptake of industry 4.0 technologies is required; and an understanding of organizational and legal challenges towards data sharing, which will assist in providing insights into the challenge of data sharing in the construction industry. If the gains of digitalization and automation are to be fully harnessed by leveraging industry 4.0 technologies, stakeholders must begin to remove individual and organizational practices that serve as barriers to the full implementation of efficient data management and assemblage in the construction industry. The authors hope that this study will create greater awareness among construction stakeholders on the need for efficient data management systems to drive the wheels of Industry 4.0 in the construction industry.

Despite the insights afforded by the study, the limitations of this study are also appreciated. Further studies could explore the level of adoption of Industry 4.0 technologies among construction stakeholders. The barriers to the uptake of digital data management practices impacting industry 4.0 technologies among stakeholders could also be explored.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Notes on Contributors

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