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Data Monetization Strategies: The Construction Industry Market Analysis

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ABSTRACT

Data monetization is leveraging data to obtain economic benefits. In the context of Big Data Analytics (BDA), data serves as a fundamental asset, enabling the transformation into valuable insights throughout various construction phases. Unfortunately, there is lack of studies focusing on data monetization within the construction industry, given the unique supply and demand characteristics among construction stakeholders. This study aims to address the objective of identifying data monetization strategies applicable to the construction industry, particularly for data sellers and data buyers. Data was gathered through a quantitative survey among 100 construction practitioners in Malaysia, encompassing developers, contractors, consultants, government agencies, technology providers, and academia. Respondents were further categorized into data sellers and data buyers. The data were analyzed using mean analysis, t-test and Spearman's rank correlation coefficient. The study identified six data monetization strategies, comprising 19 determinants. The analysis revealed high preference on all data monetization strategies and moderate differences in the preferred strategies between data sellers and buyers. Significant differences were found in 3 determinants which are (1) trading data to facilitate decision-making, (2) trading data for construction reports, benchmarks, and indices, and (3) selling visualized data on real-time platforms. The t-test indicated that data sellers are more inclined towards the three strategies for effective monetization. Furthermore, Spearman's correlation coefficient revealed the 3 determinants also positively influence another 3 determinants of (1) data wrapping to reflect better service from data provider, (2) buying raw data with its inherit information and (3) monetizing internal data to optimize organization's work process. The insights enable stakeholders to implement mechanisms that foster data monetization within project cultures accelerating BDA undertakings. Future recommendations include using larger sample sizes to enhance generalizability and to explore more areas such as construction contracts, cost, health, and safety.

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1. Introduction

Data is the new economic commodity. Organizations with data and the expertise to utilize data effectively will gain a competitive edge in the Big Data Analytics (BDA) era. Data monetization refers to using data from internal and external data sources in return of a quantifiable economic benefit (Teece & Linden, 2017; Wixom & Ross, 2018). Data is a form of information which can be exchanged and re-produced to fit into a new building blocks of information (Ofulue & Benyoucef, 2022; Zhang et al., 2023). This way, data value varies by the way one uses is or how one combines it. Data monetization perusals offers monetary avenues of selling data, trading data, or optimizing their operations to reduce costs (Najjar & Kettinger, 2013; Thomas & Leiponen, 2016; Woerner & Wixom, 2015). From a business perspective, data monetization transform business models in which revenue generation, cost structure, value proposition and relationships change. Moreover, data generate competitive advantage for businesses by enabling new revenue streams and enhancing service delivery to clients.

Previously, conventional data monetization has been achieved through the sale of raw data (e.g., material costs) and insights (e.g., tender price indices) presented in industry reports and handbook publications. With the proliferation of digital technologies such as Big Data Analytics (BDA), Internet of Things (IoT), and Artificial Intelligence (AI), data monetization has become a formal discipline where data models has been developed beyond the conventional data approaches. This change gives rise to the concept of data monetization, which is seen as the next frontier in the digital transformation (Wixom & Ross, 2018). Exponential adoption of modern technologies to optimize work process contribute data monetization is a vibrant data marketplace, with estimated value of $12 billion annually (Mehta et al., 2022).

Due to the advancement of data analytics techniques, organizations change their way of dealing with the data and started to integrate data from multiple external sources with internal data. Data is the fundamental asset for BDA undertakings. BDA is the knowledge domain harnessing data across the phases of data generation, data acquisition, data pre-processing, data storage, data analysis, data visualization, and data exposition to strategically turn data into valuable insights (Bilal, Oyedele, Qadir, et al., 2016; Faroukhi, El Alaoui, et al., 2020). Harnessing and leveraging data allows organizations to benefit from optimize productivity through automated and efficient processes (Abioye et al., 2021; Akinosho et al., 2020; LaValle et al., 2010; Owolabi et al., 2020) and create enhanced or completely new data-driven value propositions (Parvinen et al., 2020; Ram et al., 2019). Together, these forms a powerful source of competitive advantage to business organizations in modern and agile business landscape.

BDA research area in the construction industry has been the interest of many for the past 10 years. The progression is further supported by government's positive interest for the industry to move forward with BDA (Construction Industry Development Board, 2020). Exploration on BDA literature includes- 1) BDA potentials across niche construction work processes; 2) construction data analytics model (Bilal et al., 2019; Bilal, Oyedele, Akinade, et al., 2016; Gbadamosi et al., 2020); 3) BDA capabilities (Maaz et al., 2018; Ngo et al., 2020; Ram et al., 2019; Reyes Veras et al., 2022). Despite rapid research development, BDA adoption among construction organization viewed in limited (Chaurasia & Verma, 2020; Ismail et al., 2018; Ngo et al., 2020). Two underlying issues identified were the availability of digital construction data and organizational BDA adoption capability. To enhance BDA adoption in the construction industry, several research looked into technology maximization through Building Information Modelling (BIM) (Fazeli et al., 2021; Ghorbany et al., 2023), Common Data Environment (CDE) (Preidel et al., 2016; Radl & Kaiser, 2019; Tan et al., 2023), Blockhain (Kiu et al., 2020; Qian & Papadonikolaki, 2020) as well as research from soft management aspect on organizational capabilities (Ngo et al., 2020; Ram et al., 2019; Reyes-Veras et al., 2022) and data driven culture (Hashim et al., 2024). The identified research area centers on facilitating avenues for construction stakeholders to share construction data. Recognizing the value of construction data, stakeholders are positioned strategically to benefit economically from data monetization. This approach not only accelerates the adoption of BDA but also aid conventional construction business model transformation.

However, there are limited data monetization studies that focus on the construction industry. Particularly, there is a lack of understanding on how to monetize data effectively in appraisal of the unique supply and demand characterization among construction stakeholders. Consistently, Günther et al., (2017) and Najjar & Kettinger (2013) highlights the need to address effective strategies to support cohesive data monetization efforts. Thus, current limited attention on data monetization in the construction management academic literature suggest step towards data monetization can be very challenging for construction stakeholders were construction stakeholders struggle to extract economic value from their data.

As a result, this study aims to answer the following research question of – What are the relevant data monetization strategies for the application in the construction industry. The findings of this paper contribute to the body of knowledge and practice by identifying relevant data monetization strategies for the application in the construction industry. Cohesive selection of data monetization strategy appraising the variation nature of construction stakeholders business model further is key to effective balance of the construction data ecosystem. With fluid data transaction, this in return shall drive the BDA advancement in the construction system. The findings address the existing gap of BDA analytics advancements and capabilities among construction stakeholders.

2. The Data Monetization Ecosystem

2.1 Roles in Data Monetization Ecosystem

Data monetization ecosystem is rooted to the classical theory of supply and demand. An effective data monetization ecosystem is represented at an equilibrium state where "supply and demand are classically given by an observable, operational, monetary value: the buyer's maximum willingness to pay and the seller's minimum willingness to accept" (Inoua & Smith, 2020). In general, data buyer is the party representing the demand side with interest in purchasing construction data and data seller is the party representing the supply side which allows buyer to purchase, use or alter construction data of interest (Mehta et al., 2019). Figure 1 shows key roles in data monetization ecosystem from a supply and demand perspective.

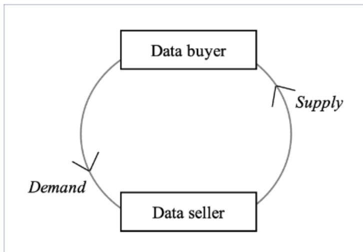

Figure 1 Key supply and demand roles in data monetization. Adapted from O'brien, London and Vrijhoef (2004)

The classical theory of supply and demand outlines, a minimum presence of data sellers and buyers is necessary to establish a data monetization ecosystem (Ofulue & Benyoucef, 2022). Roles within the data monetization ecosystem extends to entities of data sellers, data buyers, data brokers, data aggregators, data custodians, data facilitators, and data managers (Faroukhi, El Alaoui, et al., 2020; Thomas & Leiponen, 2016).

2.1.1 Data Seller

Data sellers are entities within the data monetization ecosystem that supply or sell internally owned data to third parties. This entity contributes to data maximization process as well as facilitating data-driven decision-making processes for other organizations. Data seller can opt to sell raw data in its original form or selling analyzed data enriched with insights (Najjar & Kettinger, 2013). (Thomas & Leiponen (2016) details data providers often monetize original, raw, or aggregated data with minimal effort required to make it available. While such data embodies rich information it is typically considered the least strategic and least valuable product due to the limited value-added activities involved (Bohé et al., 2013). Thus, in terms of data monetization return, data sellers generate the least amount of revenue.

In the construction industry, government entities and regulatory bodies are recognized as data sellers. Table 1 details the data monetization roles among construction stakeholders. The Table 1 shows two streams of data sellers: namely government bodies (Ministry of Works and Public Works Department) and private organization (Arcadis). These stakeholders monetize data through book publication, reports, and online data platforms. These initiatives aim to enhance productivity within the construction industry while promoting a healthy and competitive business environment. Notably, data sellers in the construction industry monetize data as open data, which is freely accessible to construction stakeholders.

Table 1 Data monetization role among construction stakeholders

Data Monetization Role	Construction Stakeholder	Country	Initiatives
Data seller	Ministry of Works Public Works Department	Malaysia	Technical documents publication (Road statistics, schedule of rates, BIM data specifications) (Ministry of Works Malaysia, 2024; Public Works Department Malaysia, 2024)
	Arcadis	Malaysia, China, Hong Kong, Philippines, Singapore, Vietnam, Indonesia	Construction Cost Handbook (Arcadis, 2024)
Data buyer	Developers Consultants Contractors Local authority Government bodies	-	-
Data Broker	National Construction Cost Centre (N3C)	Malaysia	National Construction Cost Centre (N3C) online data platform (Building material price, labour wage, machine hire rate, tender price index) (Building Cost Information Services Malayia, 2024)
	Building Cost Information Service	United Kingdom	Books publication (Price book) and online data platform (Building maintenance data, project life cycle data, carbon materials data, terms of contract data) (Building Cost Information Service, 2024)

2.1.2 Data Buyers

Data buyers are entities within the data monetization ecosystem that express interest in purchasing data. This entity plays a crucial role in driving demand for data. Data buyers have the option to acquire data directly from data sellers or through intermediary third-party entities, in exchange for financial return or renumeration of equal value. (Hanafizadeh & Harati Nik, 2020) emphasize organizations are keen to engage as data buyers to have real-time knowledge access and gear effective organizational performance as well as first mover advantage within the competitive market segments.

Construction industry distinguishes itself as a unique environment characterized by the development of one-off projects. While stakeholders may encounter similar project types, there is often variability in the composition of project teams, including developers, consultants, and contractors. This variability is especially evident in government projects procured through open tenders. Consequently, roles of data buyers in the construction industry becomes interchangeable, meaning that stakeholders such as developers, consultants, contractors, government agencies and local authorities can engage as data buyers.

2.1.3 Data Brokers

Data brokers refer to the third-party entity in the data monetization ecosystem. The entity intermediaries who purchase data from data sellers and engage in value creation activities to enhance the original raw data before selling it to data buyers. Data brokers leverage data to generate measurable economic advantages and revenue streams. Further popular terms representing value creation activities are 'converting the intangible value of data into real value' (Najjar & Kettinger, 2013) and 'turning data insights into action' (Manyika et al., 2011). As outlined in Najjar & Kettinger (2013) and Parvinen et al., (2020), value creation activities involve the process of collecting, brokers harness specialized expertise in identifying the value embedded within the data monetization ecosystem. They possess technical and analytical proficiencies to discern correlations, uncover efficiencies, and visualize complex relationships, thereby augmenting the value of data (Thomas & Leiponen, 2016). cleaning, organizing, and integrating various data types to unlock the inherent value of raw data, leading to tangible benefits. Data

Furthermore, data sellers may also assume the role of data buyers when dealing with data brokers, highlighting the multifaceted nature of their involvement (Zhang et al., 2023). Academic research identifies data aggregators and data facilitators as similar taxonomies to data brokers, underscoring their significant roles in the data monetization process (Faroukhi, El Alaoui, et al., 2020; Liu & Chen, 2015; Ofulue & Benyoucef, 2022; Parvinen et al., 2020). In industry practice, the scope of data brokers extends beyond mere provision of data. Concerns regarding the role of data brokers encompass the fundamental function of offering data as a service to data buyers. Thus, the representation of data brokers transcends traditional stakeholder roles, and can be manifest as technological platforms dedicated to selling data.

In the construction industry, specialized data providers are viewed serving the data brokers role. A prime example includes the Building Cost Information Service United Kingdom (BCIS) and Building Cost Information Services Malaysia (BCISM). These entities curate a wide array of data offerings encompassing building maintenance, project life cycle, carbon materials, contract terms, tender price index, and construction rates. BCIS and BCISM innovate the traditional data monetization approach and spearhead the international data broker role by leveraging advanced data visualization technologies such as Tableau and PowerBI to enhance the value of their construction data offerings. Figure 2 shows the N3C visual analytics of construction data. Leveraging the digital transformation in the construction sector, BCIS and BCISM provide real-time access to analyzed data through engaging visual representations. In contrast to data sellers, data brokers typically offer data access to data buyers through minimal subscription fees.

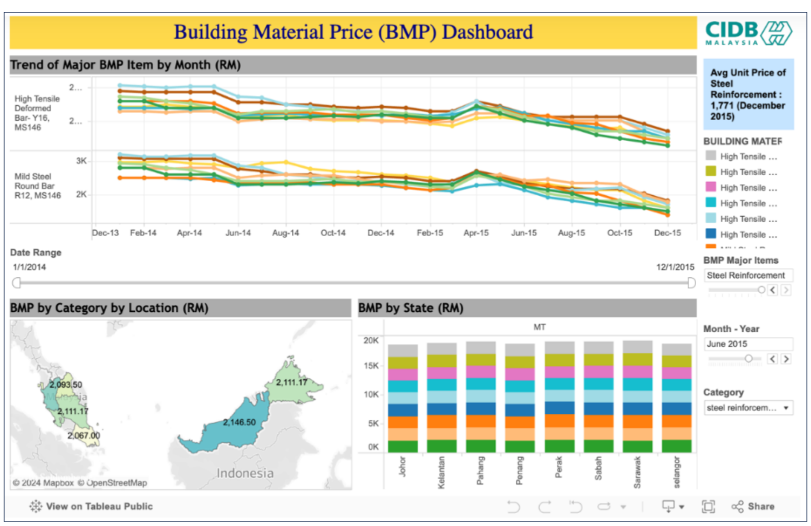

Figure 2 N3C visual analytics of construction data (Construction Industry Development Board 2020)

2.1.4 Selling Insights

Strategy has become a significant focus in recent data monetization research within the domain of Big Data Analytics (BDA) literature. To drive an effective data monetization ecosystem, it is crucial to understand the determinants that limit and facilitate supply and demand traction within the specific construction industry context. Characterization or supply and demand in the construction industry is reflected to the role of specific construction stakeholders, participating as data seller and data buyers.

In construction business models, two primary roles are identified: stakeholders involved in product delivery (e.g., clients or developers selling construction buildings) and stakeholders involved in services delivery (e.g., consultants, contractors, and suppliers providing professional services). Each stakeholder specializes in different areas and pursues distinct organizational goals. However, in delivering a construction project, these stakeholders collaborate to achieve a common goal of building quality, cost-effective construction projects with timely delivery. The variations of business models, organizational goals and construction work processes working collaboratively toward a common objective represents the unique characteristics of data monetization in this industry. Such uniqueness suggests an implication in terms of different preference on data monetization strategy among the data seller and data buyers.

2.2 *Data Monetization Strategies*

In the dynamic and competitive modern business landscape, organizations confront ongoing pressure from the market and the looming threat of disruption (Parvinen et al., 2020). This pushes business organizations to innovate conventional business processes, ensuring the curation of relevant products and services to maintain market relevance. With the advent of digital transformation and the rise of big data analytics technology, Zhang et al., (2023) and Wixom (2014) viewed a growing number of organizations seizing the opportunity to leverage data value as a new revenue stream.

Extensive studies into the domain of data monetization, consistently highlighting three key areas: 1) Internal and external monetization approaches, 2) Data monetization strategies, and 3) revenue models. Figure 3 illustrates the data monetization ecosystem based on previous literature. A coherent data monetization strategy and revenue model improves construction organization's capability to materialize specific economic value. While commonly associated with revenue creation through the discovery, capture, storage, analysis, dissemination, and utilization of data (Liu & Chen, 2015); Data monetization extends beyond mere data selling. Often overlooked, organizations evaluating data can engage in two types of data monetization activities namely, internal, and external monetization.

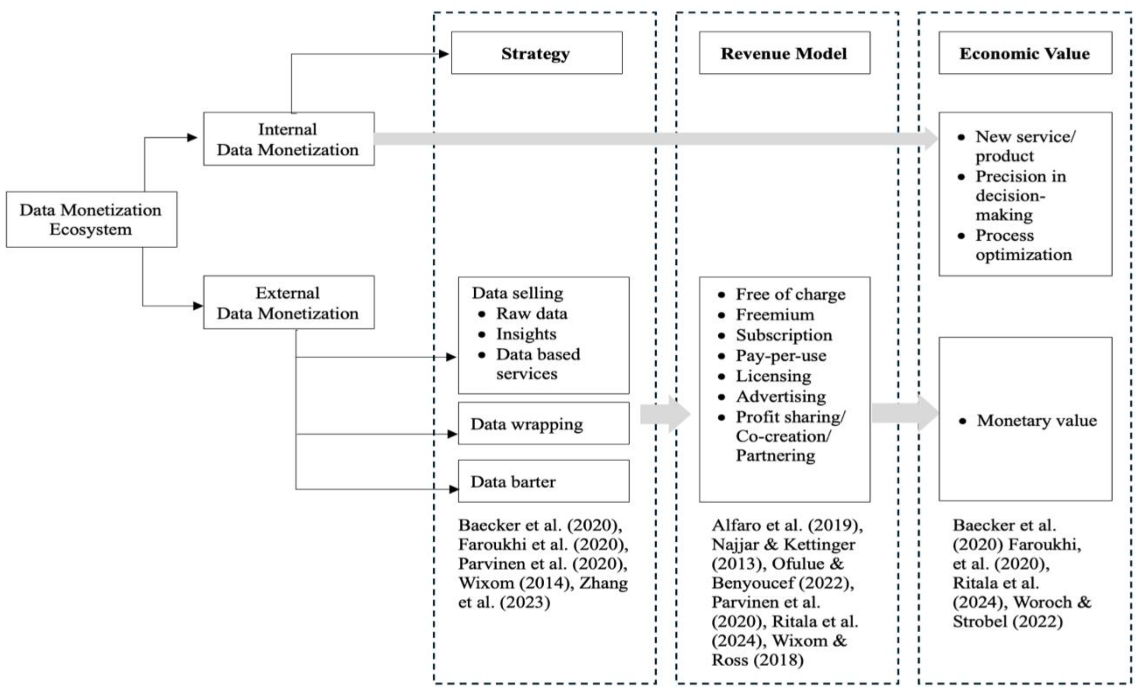

Figure 3 Data monetization ecosystem

Internal monetization involves activities of maximizing data within an organization to optimize processes, enhance decision-making precision, and innovate new services or products. This form of data monetization aims to extract and maximize the value of data in exchange for economic benefits to the organization. Apart from revenue generation, organizations pursue internal data monetization to boost productivity, reduce operational cost enhance business agility, and reputation improvement (Alfaro et al., 2019; Liu & Chen, 2015; Najjar & Kettinger, 2013; Ofulue & Benyoucef, 2022). In contrast, external data monetization as frequently highlighted in academic literature, entails maximizing data to benefit other organizations while yielding returns. Parvinen et al., (2020) and Zhang et al., (2023) further deliberate external data monetization through apprehension of direct and indirect data monetization strategies. The former involves the direct sale of data, while the latter focuses on process efficiency enhancements or product improvements reliant on data.

2.2.1 Data Selling

Data selling involves data suppliers selling data directly to external organizations, thereby creating new revenue streams. The data selling strategy is the preferred and straightforward form of external data monetization strategy. With the acquired data, data buyers are able to gain new knowledge, understand meaning behind data pattern and validating interorganizational insights which would not been accessible (Alfaro et al., 2019). Data selling strategy requires technology transformation budget such as data infrastructure platform (cloud services, platforms), analytical services, visualization technology and contracting cost (i.e., non-disclosure agreement, data sharing and purchase contracts) (Faroukhi, Alaoui, et al., 2020; Najjar & Kettinger, 2013).

Three primary data selling strategies include selling raw data, selling insights, and selling data-based services. Selling raw data involves tapping data directly from the storage layer without the process of parsing, cleaning, or cataloguing data in return of money (Arent van't Spijker, 2014). Conventionally, data buyers can access data in the form of data files or publication. However, with ongoing digitalization in organizational workflows, data buyers can now receive real-time data through dashboards. Raw data may not hold significant meaning for data buyers, as its utilization demands a high level of data literacy and analytical capabilities for extracting value or effectively utilizing the data. Therefore, selling raw data should be complemented by a robust business model that packages data with relevant aggregation and finds the optimal balance between meeting data buyer needs and their willingness to pay (Najjar & Kettinger, 2013; Ritala et al., 2024).

Selling insights involves data sellers offering analyzed data, such as insights, to data buyers. This strategy effectively addresses data security and privacy concerns between data sellers and buyers by restricting access to the original data (Arent van't Spijker, 2014; Thomas & Leiponen, 2016). In terms of insights value, it extends beyond the volume and real-time data obtained by the data seller. Typically, the value of insights is directly proportional to the data seller's ability to source data from various operations and processes (Ritala et al., 2024). Leveraging insights enables data buyers to enhance overall business agility and performance promptly and efficiently. Faroukhi, El Alaoui, et al., (2020), Hanafizadeh & Harati Nik (2020), Parvinen et al., (2020) and Yuan et al., (2024) highlight selling insights provides significant benefits for market understanding and decision-making support. Data buyers can realize potential advantages in cost reduction, fraud prevention, waste reduction, risk mitigation, supply chain optimization, enhanced customer service, improved customer experience, increased market share, and bolstered customer loyalty. In comparison to selling raw data, selling insights limits data buyers' flexibility and adaptability in extracting value from the data (Parvinen et al., 2020).

Selling data-based services refers to consultancy services provided by data sellers to analyze, predict, and optimize data buyers' work processes and business environments (Ofulue & Benyoucef, 2022). Typically pursued by technology providers or data analytics services companies (Ritala et al., 2024), this strategy contributes insights or workflow solutions from analyzing and understanding data buyers' work processes. Data-based services facilitate continuous improvement by leveraging the extensive pool of data contributed by both data sellers and buyers.

2.2.2 Data Wrapping

Data wrapping strategy is an extension of the data selling strategy. To increase the value of data or differentiate data offerings in the market, data sellers wrap information around other existing core products and services offered by data sellers (Wixom & Ross, 2018; Woerner & Wixom, 2015). This strategy reflects the data seller's strategic business model in identifying information gap or need in the market. In return, the combination of information with existing core products or services creates added value and enhances attractiveness to data buyers. Commonly, data sellers do not charge extra for data wrapping; instead, the information provided is offered free of charge to increase market share or strengthen relationships with data buyers.

2.2.3 Data Bartering

Data monetization involves the exchange of data between data sellers and data buyers in exchange of economic benefit. The economic benefit extends towards monetary remuneration and non-monetary rewards. Data bartering strategy is the exchange of raw data or insights for information products and services such as reports, benchmark metrics, and analytics software (Woerner & Wixom, 2015). To facilitate effective data bartering strategy, data sellers and data buyers shall commit to a centralized data exchange process. This process manages contractual, regulatory, and legal requirements accountability to safeguard data from being distributed, integrated, shared, and used in the future that would risk the firm's reputation (Wixom, 2014).

2.3 Monetizing Project Management Data

Big Data Analytics has had significant attention from researchers through the use of data engineering and computation (Shubham et al. 2023), blockchain and InterPlanetary File System (IPFS) (Adel et al. 2023), and Digital Twin Information System (Tanga et al., 2022) together with machine learning or artificial intelligence techniques. (Wu and Abourizk, 2021) believes that the future of digitalization in construction is the enhancement of data value. Data monetization has the ability to generate great benefits for project management in construction.

According to Huang et al. (2021), the important aspect of data monetization is identifying valuable data assets in construction projects. Project data such as cost estimates, schedules, material usage, and equipment performance has significant value that can be monetized, hence the importance of identifying the potential data sources. As the data can then be utilized to improve decision-making, increase efficiency, and improve project outcomes, construction organizations may begin developing data-driven products and services. Construction firms can analyse their project data to develop new products and services that meet specific market needs. For example, data from past projects can be used to create more accurate cost estimates and schedules for future projects.

Ultimately then construction companies may sell the project data to interested parties such as researchers, suppliers, or other construction firms. This direct monetization of data can generate additional revenue streams to the organizations. Strong establishment of data governance may also be achieved as effective data monetization requires robust data governance policies to ensure data quality, security, and compliance with regulations. Project managers shall play a key role in establishing these policies and ensuring data is managed consistently across projects.

The effort does come with multiple challenges including data security, privacy, and quality (Shubham et al. 2023), intermediated workflows, human errors, transfer latencies, inaccuracies, information holes (Adel et al. 2023) and the low implementation of machine learning for construction data (Wu and Abourizk, 2021). Nevertheless, construction project managers play a vital role in data monetization by identifying valuable data assets, improving decision-making, developing new products and services, and establishing effective data governance policies. The embrace of data monetization can unlock new revenue streams and gain a competitive edge for construction organizations in the industry.

In contemporary business literature, data monetization occurs within both business-to-business (B2B) and business-to-customer (B2C) markets. B2C data monetization is prevalent in data-driven businesses (Acciarini et al., 2023; Hartmann et al., 2016; Woroch & Strobel, 2022) which convert customer data into insights and sell it for a profit., this study focuses on data monetization from the B2B market. In the relevance to understand the context of data monetization in the construction industry construction projects predominantly involves internal stakeholders (i.e., client, financier, project management team, and contractors) as well as external stakeholders (i.e., local government, owners, and environmentalist) (Nash et al., 2010). This shows the majority of stakeholders involve are in the form of business organizations, with a minority of individual customer. Thus, this study shall focus on data monetization in the construction B2B market context, with interest on project management data.

3. Methodology and Data Representation

This study investigated the data monetization strategies preference in the Malaysian construction industry by utilizing quantitative method approach. Data was gathered through an extensive review of literature and insights from key stakeholders involved in Malaysian construction projects (including Developers, Contractors, Consultants, government agencies, technology providers, and academia). Primary data collection was initiated by a preliminary study using pilot questionnaire to ensure clarity and content validity. The questionnaire was structured into three main sections: (1) demographic information of respondents; (2) selection of data monetization strategies; and (3) preferences regarding revenue models. The actual survey was then conducted among project practitioners in Malaysia who serve as both data providers and users.

The collected data were analyzed using SPSS software version 26.0. General respondent information, along with standard deviation and mean scores, were assessed using descriptive statistics (frequency and mean analysis). Cronbach's alpha coefficient was employed to ensure the reliability of the variables, with values ranging from 0 to 1; higher values denote more reliable groupings (Vaske et al. 2017). A Cronbach's alpha exceeding 0.7 is considered "good" or "acceptable" for reliability testing. Subsequently, an independent sample t-test is a statistical test was used to compare the means of the two different groups (data sellers and data buyers) to determine if they are significantly different from each other (Mendoza, 2023). The association between the dataset is then measured using Spearman's rank-order correlation, which is a nonparametric measure of the strength and direction of ranking between two respondent groups on an ordinal scale (Schober and Schwarte, 2018).

A total of 100 questionnaires were distributed via email, social media, and interviews. Responses were collected on a five-point Likert scale ranging from one (strongly not preferred) to five (strongly preferred), resulting in 67 valid responses and an effective response rate of 67%. Based on the survey conducted and general statistical analysis using SPSS software, the distribution across sectors was as follows, 9% were from governments, 4.5% were from academia,14.9% were from tech provider, 32.8% from contractor, 19.4% were from consultant and 19.4% were from developers. Table 2 details the organizations' profile. Regarding the experience of participants, 37.3% have more than 20 years, 35.8% have between 10-20 years, 11.9% have between 5-10 years and 14.9% have less than 5 years' experience in the industry. Furthermore, 61.2% were presenting data buyers while another 38.8% were presenting as data sellers. As for the organization values, majority of the respondents are in organization with more than RM5 million in value.

Table 2 Profile of the organizations

Criteria	Responses	Frequency	Percentage
Role	Data provider	26	38.8
	Data buyer	41	61.2
Total		**67**	**100**

Criteria	Responses	Frequency	Percentage
Organization business domain	Contractors	22	32.8
	Developers	13	19.4
	Consultants	13	19.4
	Technology provider	10	14.9
	Local authority	6	9
	Academia	3	4.5
Total		**67**	**100**
Organization value	< 1 million	2	3
	> 1- 5 million	10	14.9
	> 5 million	55	82.1
Total		**67**	**100**
Years of experience	0-5	10	14.9
	>5-10	8	11.9
	>10-20	24	35.8
	>20	25	37.3
Total		**67**	**100**

4. The Construction Industry Data Monetization Strategies

The context of data monetization in the construction industry was analyzed across the identified strategies in Section 2.2. A total of 19 strategies were assessed based on the questionnaire survey responses. All determinants were assessed using five-point Likert Scale. Cronbach's alpha coefficient revealed a value of 0.76, indicating a good internal consistency (Vaske et al. 2017). Almost all items in the test measure the same construct and are correlated with each other. Table 3 summarizes the mean rank analysis for each of the data monetization determinants. A ranking of data monetization strategies was carried out to determine the relative preference of different data monetization strategies perceived by construction stakeholders. Based on the ranking scores, data selling (Insights) was the most preferred strategy (4.53), followed by then data barter (4.40), internal data monetization (4.34), data wrapping (4.13), data selling (data-based-services) (4.11), and data selling (raw data) was the least preferred strategy (3.53).

Table 3 Mean rank analysis on each determinant group

Data Monetization Strategy	Code	Mean	Rank	References
Selling insights - Buying data to be incorporated in decision making process - Buying data with limited identification to its nature - Buying data to improve decision making	 INS1 INS2 INS3	4.53	1	Arent van't Spijker (2014), Thomas & Leiponen, (2016) Faroukhi et al. (2020), Hanafizadeh & Harati Nik (2020), Parvinen et al. (2020)
Data barter - Trading data to aid project management decision making - Trading data for reports, benchmarks and indices - Trading data to aid project special dealings	 DB1 DB2 DB3	4.40	2	Woerner & Wixom (2015)
Internal data monetization - Monetizing data to optimize project work process - Monetizing data to reduce operation cost - Monetizing data to improve customer service	 INT1 INT2 INT3	4.34	3	Najjar & Kettinger (2013), Liu & Chen (2015), Alfaro et al. (2019), Ofulue & Benyoucef (2022)
Data wrapping - Buying data to improve decision making value - Additional data to reflect better service from data provider - Additional data to capture BDA insights which might be overlooked	 DW1 DW2 DW3	4.13	4	Woerner & Wixom (2015), Wixom & Ross (2018)

Data Monetization Strategy	Code	Mean	Rank	References
Data-based services - Buying raw data through online real-time data platform - Buying visualized data from a real-time data platform - Buying data insights through online real-time data platform	 BDS1 BDS2 BDS3	4.11	5	Ofulue & Benyoucef (2022), Ritala et al. (2024)
Selling raw data - Buying original data directly from data owner - Buying aggregated data for its versatility - Buying data that is not being analyzed - Buying raw data with its inherited information	 RD1 RD2 RD3 RD4	3.53	6	Najjar & Kettinger (2013), Parvinen et al. (2020), Ritala et al. (2024)

4.1 Selling Insights

The results indicate selling data in the form of as the most effective data monetization strategy among construction stakeholders with highest mean score of 4.53. Selling insights is largely associated in deriving organization value when integrated in various construction decision making process particularly, in project management, cost management and safety management. Selling insight is preferred by construction stakeholders due to its contributary value in proactive decision making in comparison to decision to improve construction performance.

INS3 asked on construction stakeholders' preference to monetize data in the form of insights to limit owner information data trails ranked as the highest mean score. This finding is consistent to dude) where in general, preference to sell data in the form of insights increases data value along with limited access to data trail. In the construction industry, big data analytics adoption is often associated with poor regulation on data security and privacy measures across the established data architecture (Boyes, 2015; Braun et al., 2018; Moura & Serrão, 2015; Patel & Patel, 2020). Insights are the data produced when compliance with data architecture, performing data sourcing, filtering, storage, and analytics processes. Construction data is subjected to complex data trail as each data is associated to different layers of construction stakeholders' communications in accordance with various construction phases and is uniquely tailored to one-off construction project nature. When construction stakeholders sell data in the form of insights, data trail such as information of data owners, project location, and project price were detached from the data. Thus, effectively manage data security and privacy while increasing data value.

4.2 Data Barter

Besides selling data in the form of insights, the result indicates data barter as the second most effective data monetization strategy with a mean score of 4.40. Consistent data bartering in other industries (Hanafizadeh & Harati Nik, 2020; Woerner & Wixom, 2015), data bartering in the construction industry does not involve exchange of money. Instead, the value of data is used as a measure of worthiness when transacting data between data provider (i.e., developer, government agency, and technology provider) and data buyer (i.e., consultant, contractor, and academia). Extending to (Mehta et al., 2019), data bartering is a effective measure of data monetization strategy which complements data seller's concern on selling data as a monolithic unit (selling specific data context to a specific buyer) as well as data buyer's concern on obtaining exclusive excess to data in the pursuit of competitive advantage.

DB2 highlights construction stakeholders look beyond immediate organizational value creation when bartering data. Generally, data bartering leads to an indirect impact with its value can hardly be measured such as positive association to reputation (Hanafizadeh & Harati Nik, 2020). Interestingly, construction stakeholders view data barter as a strategy to increase competitiveness where stakeholders barter data with parties that they trust, where the value of data shall benefit all contributing parties even though, realization of value of data bartering requires time and risk taking.

Findings further unveil construction stakeholders may or may not barter data because they intend to. DB3 indicates construction stakeholder barter data as a measure to facilitate or 'smoothen' construction undertakings. This is because data is coined as the new gold. In the construction industry, data availability is a scarce resource. Appreciation of data value in the construction industry is particularly high where data is viewed as a rare commodity.

4.3 Internal Data Monetization

Internal data monetization is ranked third in effectiveness of strategy in monetizing data. In line with current BDA literature, construction stakeholders adopt analytics in specific construction application of data driven design, project management, cost management, safety management, construction waste management, facilities management, and energy management. (Ahmed et al., 2017; Koseleva & Ropaite, 2017; W. Lu et al., 2018; Y. Lu & Zhang, 2021; Meng et al., 2022; Taylan et al., 2017). Findings INT 1, INT 2, and INT 3 shows BDA adoption positively viewed among construction stakeholders where BDA investments suggest positive value realization in overall form of work process optimization, cost reduction, and organization's service or customer experience improvement. Preference towards internalizing data monetization perhaps due to the current BDA infancy particularly in the Southeast Asian construction market (Ismail et al., 2018; Ngo et al., 2020).

Findings suggest the relevance for internal data monetization as an effective data monetization strategy in lieu of the current realities of BDA progression in the construction industry. To effectively monetize data, construction stakeholders must improve analytics competency to turn raw data into insights. This requires analytics capabilities identify relevant data, integrate data, apply effective analytics techniques (i.e., artificial intelligence, machine learning, and deep learning) and visualize data (Ghasemaghaei et al., 2018). However, these skills are currently scare in the construction industry (Abioye et al., 2021). Internalization of BDA impact and value needs to set in place prior to harness strategic external data monetization efforts.

4.4 Data Wrapping

The results indicate data wrapping as a preferred data monetization strategy with the mean 4.13. Consistent with (Raddats et al., 2022; Woerner & Wixom, 2015), construction organizations pursue data wrapping as a strategy to generate higher product or services value. Findings in DWI, DW2 and DW3 shows construction stakeholders wrap existing services or products with data in gaining buying confidence or increasing decision making value. Several measures of output of data wrapping are construction work process optimization and enhancement in construction work performance. Product such as materials cost data or cost index can be wrapped around conventional processes such as measurement services which function in complementary in the overall comprehensiveness delivery of establishing high value decision making such as construction cost plan.

Hanafizadeh & Harati Nik (2020) suggest data wrapping acts as a helping stimulant for organizations to monetize data. In particular DW1 shows data wrapping strategy is valuable when the selection of data wrapped addresses the construction information gaps. Effective data wrapping requires deep and rich construction technical knowledge to identify construction product and services which complements one another which enriches the construction work process. This further strengthen Dixon et al., (2017) and Sawhney & Knight (2023) position on the critically of construction skills to enrich digitalization and BDA technology development which in return contributes to the evolving roles for construction stakeholders.

4.5 Data-Based Services

Data-based services is a relevant data monetization strategy for the construction industry with mean 4.11. Data-based services is a strategy mainly pursued by industry's technology leaders or providers (Ritala et al., 2024). Similarly, findings identify 82% of respondent suggest construction technology providers in relevance to pursue data-based services monetization. Data-based services involve a third-party to carry out the roles in monetizing data (Najjar & Kettinger, 2013; Parvinen et al., 2020). The third-party plays an independent role to protect from monetizing bias. Technology adoption in the construction industry often results to on-shelf technology services via subscription mechanism with a small number or construction stakeholders developing in-house technology services. This allows construction stakeholders to adopt technology at a lower recurring cost, as construction stakeholders are mainly of small and medium sized organizations with limited capability to venture technology innovation internally (Domnina et al., 2016). Consistent subscription presents technology providers with the opportunity to collect, store and harness valuable data sourced from multiple data owners. In line with the appreciation of data as valuable asset, technology provider fills up the role as an independent party to monetize data and enhance construction work process optimization as well as construction work performance at an industry level through data-based services strategy.

Data can be monetized through integrated data platform (data buyer purchase or access self-service from an online platform) or conventional data sharing (data provider package and share data manually to data buyer). Findings from DBS1, DBS 2 and DBS3 show construction stakeholders prefer data-based services access through integrated data platform where data buyers can access real-time data from an online platform. Findings also indicate construction stakeholders further inclined towards data-based services in the form of visualized insights in comparison to raw data.

4.5 Selling Raw Data

The results indicate selling raw data as the least strategic data monetization strategy (mean 3.53) albeit its relevance for the application in the construction industry. Raw data is the least valuable form of data due to its limited variations in application and generalizability. Selling raw data perhaps is the quickest way to monetize data (Lewis & McKone, 2016). Consistent to (Wixom & Ross, 2018), selling raw data is arguably the most challenging data monetizing strategy for organizations in business to business (B2B) markets.

Construction data are rich and unique in nature as construction projects. Even for similar building types, construction data are created differently because of size, location, time, appointment of project team members, and contractual arrangement. This rich data is valuable. While the process of monetizing raw data might be simpler for data buyers, the one-off nature of the construction projects limits the data applicability and demand for raw data. Jiang & Gallupe (2015) caution on the significant gap between the analytics and the actual business needs in attaining data value in decision making. Gaining access to raw data may be helpful for construction stakeholders. However, paucity in the construction industry BDA adoption argues the gap on a defined and established insights generation practices. This is particularly apparent whereby; development of BDA models is present in a theoretical stage and limitedly accessed by construction stakeholders. Moving forward, construction stakeholders shall be informed of comprehensive data trail as well as having a high-level technical data literacy is important when purchasing and using raw data.

5. Construction Stakeholder's Data Monetization Strategy Based on Supply and Demand Theory

Extending to the supply and demand context, data monetization in the construction industry is moderated by two domain groups namely, data sellers and data buyers. Owing to the differences in backgrounds and business objectives, this study hypothesizes a difference in monetization strategy between the two groups.

H0: There is no significant difference on data monetization strategy among data seller and data buyer.

H1: There is a significant difference on data monetization strategy among data seller and data buyer.

Independent Samples T-Test was performed to gauge the significant difference on the type of data monetization strategy among the 2 groups. Table 4 shows the Independent Samples T-Test to measure the significance of the difference in responses. The null hypothesis (H0) is that the variances of the two groups are approximately equal where the distribution of scores are similar in shape between the two groups.

The 19 data monetization strategy was assessed by Levene's Test, alongside the F statistic p-value to assess whether the variances of two or more groups are equal. Six data monetization strategies INS1, DB1, DB2, INT1, DW2 and BDS2 showed a notable significance level with p-value near 0.01. The significant F statistic in the six strategies ranging from 22.46 to 5.55 also supported the assertion of the Levene's Test to reject the null hypothesis. Thus, proving that equal variances are not assumed, hence justifying the difference in responses between the two groups.
Extremely high positive or negative (far from zero) of the "t" statistic indicates a large difference between the group means relative to the variability in the data, suggesting a significant difference between group means. The t-test reveals that DB1, DB2 and BDS2 consists of high values in the "t" statistics ranging from 5.61 to 2.83, which supports the rejection of the null hypothesis. The findings were further supported by the high degrees of freedom indicating a t-distribution that is close to a normal distribution, two-tailed p-values of ≤ 0.05 indicating a significant difference, positive mean difference which indicates that the mean of the first group (Data Buyer) is greater than the mean of the second group (Data Provider).

The standard error differences are below 0.24 which is near to 0. It indicates that the sample means are close to the true population mean difference, implying precise estimates. The 95% Confidence Interval of the Difference provides an estimated range of values for the difference between the means of two populations. Based on Table 4, most of the intervals include zero suggesting that the difference between the population means is not statistically significant, meanwhile the intervals in DB1, DB2 and BDS2 does not include zero, suggesting that there is a significant difference between the population means at the 95% confidence level.

Table 4 Independent samples T-test

Variables	Equal variances assumed/ not assumed	Levene's Test for Variance Equality		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
INS1	a.	5.55	0.02	1.52	65.00	0.13	0.21	0.14	-0.07	0.49
	b.			1.43	42.97	0.16	0.21	0.15	-0.09	0.51
INS2	a.	3.75	0.06	-1.46	65.00	0.15	-0.32	0.22	-0.76	0.12
	b.			-1.68	61.85	0.10	-0.32	0.19	-0.70	0.06
INS3	a.	0.38	0.54	-0.34	65.00	0.73	-0.05	0.14	-0.33	0.23
	b.			-0.35	55.79	0.73	-0.05	0.14	-0.32	0.23
DB1	a.	10.88	0.00	5.43	65.00	0.00	0.95	0.17	0.60	1.30
	b.			4.65	31.32	0.00	0.95	0.20	0.53	1.36
DB2	a.	22.46	0.00	3.32	65.00	0.00	0.69	0.21	0.28	1.11
	b.			2.83	30.77	0.01	0.69	0.24	0.19	1.19
DB3	a.	4.94	0.03	1.06	65.00	0.29	0.25	0.23	-0.22	0.71
	b.			0.96	37.95	0.34	0.25	0.26	-0.27	0.77

Variables	Equal variances assumed/ not assumed	Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
INT1	a.	9.71	0.00	0.93	65.00	0.36	0.19	0.21	-0.22	0.61
	b.			0.84	38.37	0.40	0.19	0.23	-0.27	0.66
INT2	a.	4.75	0.03	0.95	65.00	0.34	0.20	0.21	-0.22	0.63
	b.			0.87	39.59	0.39	0.20	0.23	-0.27	0.68
INT3	a.	0.02	0.88	4.09	65.00	0.00	0.76	0.18	0.39	1.13
	b.			4.01	49.81	0.00	0.76	0.19	0.38	1.14
DW1	a.	1.95	0.17	0.56	65.00	0.57	0.12	0.22	-0.31	0.55
	b.			0.59	61.15	0.56	0.12	0.21	-0.29	0.53
DW2	a.	8.36	0.01	2.57	65.00	0.01	0.39	0.15	0.09	0.69
	b.			2.64	57.40	0.01	0.39	0.15	0.09	0.69
DW3	a.	4.02	0.05	-0.76	65.00	0.45	-0.17	0.22	-0.61	0.28
	b.			-0.82	64.23	0.42	-0.17	0.21	-0.58	0.24
BDS1	a.	0.28	0.60	1.75	65.00	0.08	0.44	0.25	-0.06	0.94
	b.			1.74	52.29	0.09	0.44	0.25	-0.07	0.95
BDS2	a.	9.93	0.00	5.61	65.00	0.00	1.03	0.18	0.66	1.40
	b.			5.17	39.84	0.00	1.03	0.20	0.63	1.43
BDS3	a.	4.40	0.04	1.51	65.00	0.14	0.20	0.13	-0.06	0.46
	b.			1.44	45.90	0.16	0.20	0.14	-0.08	0.47
RD1	a.	0.02	0.88	0.62	65.00	0.54	0.15	0.24	-0.32	0.62
	b.			0.60	47.65	0.55	0.15	0.24	-0.34	0.63
RD2	a.	1.30	0.26	1.65	65.00	0.10	0.43	0.26	-0.09	0.95
	b.			1.70	58.47	0.10	0.43	0.25	-0.08	0.93
RD3	a.	0.20	0.66	-2.16	65.00	0.03	-0.57	0.27	-1.10	-0.04
	b.			-2.15	52.76	0.04	-0.57	0.27	-1.11	-0.04
RD4	a.	1.26	0.27	8.39	65.00	0.00	2.17	0.26	1.65	2.68
	b.			8.31	51.54	0.00	2.17	0.26	1.64	2.69

Aside from the independent sample t-test, Spearman Correlation test was also performed. The test revealed a strong positive correlation between BDS2 and DW2 (0.4), DB1 and RD4 (0.5) as well as DB2 and INT1 (0.4). The positive correlation coefficients indicate that there is a positive monotonic relationship between the two variables in a manner that as one variable increases, the other variable tends to also increase (Schober and Schwarte, 2018).

In general, all 19 data monetization strategies show moderate significant difference in response between Data Seller and Data Buyer. The strategies with positive mean differences prove that the mean in Data Buyer increases as the mean of Data Provider increases. Meanwhile, strategies with negative mean difference show vice versa. Other than that, BDS2, DB1, and DB2 have relatively high "t" statistics indicating significant difference between the groups. Other measures such as degree of freedom, Sig. (2-tailed), mean difference and confidence intervals are coherent with the scores in the "t" statistics.

While there is no major significant difference on data monetization strategies between the two groups in general, high p-value for strategies BDS2, DB1, and DB2 shows notable differences on the preference of effective data monetization strategies. Besides that, the strategies also are positively correlated with DW2, RD4 and INT1. The finding indicates avenues of concerns or opportunities to be leveraged by data sellers on the appropriate strategy to monetize data in the construction industry context. Findings highlight high preference in terms of digitalization access when buying construction data. When pursuing selling data through data-based services strategy, data sellers shall be more considerate in providing data buyers a self-service data access option through an online data platform. The presence of digital networks is key to reliable data access interaction between various stakeholders (Faroukhi, Alaoui, et al., 2020). Construction stakeholders who are pioneering technologies such as BIM, Big Data Analytics, Common Data Environments, IoT, and Blockchain perceive a competitive advantage in monetizing data. These organizations are actively creating, storing, and managing digital construction data, positioning them favorably in the market.

Furthermore, data buyers show high appreciation to visualized data in comparison to conventional data list. Such appraisal in lieu to visualized data in providing sharp, deep and easy interpretation when communicating data. Visualized data improves data understanding by reducing 'construction blocks' among construction stakeholders while enriches the capability to make fast decision to facilitate real-time remote control both on construction project level and operation level (Mauri, 2022; Wu et al., 2019). Visualization of data also influences the use of data wrapping, where additional suggested data is reflecting positive service by data provider (Wixom & Ross, 2018). Data wrapping involves contextualization, visualization, enrichment, customization, and personalization of data, making the data more actionable and demonstrating a high level of service to their clients.

DB1 and BD2 further indicate data bartering is especially valuable when construction stakeholders are able to capitalize data in delivering both short-term and long-term value to the organizations. Whilst rated as the second most preferred data monetization strategy in general, data buyers show interest towards short-term data bartering value in optimizing time taken within a construction project decision making process.

In terms of long-term value for construction stakeholders, business sustainability in the 21st century relies on innovation extending beyond merely technological development. Innovation in the modern world primarily addresses the assimilation of transformative technology into a specific organization's business process. Findings further aligns with the role of data as an asset in creating a fundamental shift towards data-driven innovation (Faroukhi, Alaoui, et al., 2020; Hartmann et al., 2016; Moro-Visconti, 2020) which enhances organization's business model agility (Laitila, 2017; Yuan et al., 2024). In the construction industry, data monetization is viewed in complementary to current progressive Big Data Analytics uptake. Besides positioning as key accelerators for construction stakeholders to pursue data driven decision making, strategic alignment of data monetization strategy to construction stakeholder's business process to innovate new forms of professional construction services or products (i.e., construction materials) to the customers as well as intra industry collaboration.

The DB1 and DB2 in data barter are also positively correlated to RD4 in raw data selling and INT1 in internal data monetization. When organizations purchase raw data, they gain access to the original, unaltered data collected directly from the source. Raw data has the advantages of being accurate, flexible, and comprehensive. Trading data is crucial for making informed decisions in trading and investment contexts and the positive correlation between raw data and trading data enhances project management decision-making in performing enhanced analysis, informed decisions, project planning, execution, and monitoring. As internal data monetization involves using an organization's internal data, this approach can optimize various work processes and is positively correlated with trading data for construction reports, benchmarks, and indices. Both strategies can be optimized in enhancing decision making, increasing efficiency, innovating the best practices in project management, and enabling accurate market positioning.

Importantly, significance highlighted across BDS2, DB1, and DB2 monetization strategies postulate the element of trust at the center of monetizing data between data sellers and data buyers in the construction industry. Construction projects are high risk in nature where stakeholders of different business processes and aims having to work collaboratively under complex communication hierarchy. To this, trust is the key determinant to successful projects and crucial to effective build relationship between integrated project teams (Gad & Shane, 2014).

Within the construction industry interpretation, the root of trust is rooted to attributes of honest communication, reliance, and faith in delivery outcomes (Khalfan et al., 2007). While data is argued as pristine commodity contributing to the negative data sharing perception among construction stakeholders (Ayodele & Kajimo-Shakantu, 2022; Tan et al., 2023), findings on BS2, DB1, and DB2 shows that construction stakeholders are willing to share data with mechanism of trust in place. BS2 indicates the relevance to technology as means to provide transparency mechanism data tracking, contracting, and transferring resources between data sellers and data buyers (Qian & Papadonikolaki, 2020). DB1 and DB2 further implicate data barter as a mechanism which symbolizes trust, aiding key trust building elements of reciprocity particularly when organizations involved are working towards similar goal (Khalfan et al., 2007). Hence, findings accentuate that data sharing as precursor to monetizing data in the construction industry is not an impossible agenda. Dealings involving data shall be moderated with strategic mechanism involving the interweave between BDA technology adoption within soft management aspect. In return, this shall contribute to a cohesive supply and demand of construction data monetization ecosystem.

6. Conclusion and Recommendation

This study identified 6 data monetization strategies represented by 19 determinants in understanding how construction stakeholders shall best pursue monetizing data. Strategic adoption of data monetization efforts viewed to improve BDA capabilities and adoption in the construction industry. It was found that all 6 data monetization strategies in the general literature are relevant for the construction industry application. The order of importance was determined by the mean rank analysis – in descending order- INS, DB, INT, DW, BDS, and RD. Based on the survey, results from the independent samples t-test highlights no apparent differences in the data monetization preferred from data sellers and data buyers. The research findings suggest that, despite representing different organizational backgrounds, participants from various sectors (Government, Academia, Tech providers, Contractors, Consultants, and Developers) share similar perspectives on data monetization strategies in the Malaysian construction industry. Slight differences were found in determinants DB1, DB2 and BDS2. This further indicates construction data sellers shall be more considerate to DB1, DB2 and BDS2 data monetization strategies to effectively monetize data. Besides that, the Spearman's rank correlation coefficient also suggests that the 3 determinants have strong positive influence on another 3 determinants which are DW2, RD4 and INT1. The 6 determinants had been identified to possess unique statistical divergence within all the 19 determinants, thus highlighting the critical need for further detailed investigation.

This study is limited to a few areas. In terms of the sample size, the questionnaire sample is relatively small. The research only covers construction stakeholders with representation to supply and demand role in a specific geographical context of Kuala Lumpur. A larger sample size may increase the generalization on data monetization strategies identified in this research. In addition, the survey questionnaire was designed to conduct a understanding of the effective data monetization strategies among construction stakeholders specific to construction project management data. Further studies can investigate the similar with focus in niche areas of construction contractual data, construction cost data, as well as construction health and safety data.

These insights contribute to a better understanding of data monetization strategies in the construction industry, enabling practitioners to implement measures that promote data monetization within project cultures. Ultimately, this can lead to accelerate BDA undertakings, addressing the specific challenges encountered in Malaysia's construction sector.

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References

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial Intelligence in the Construction Industry: A Review of Present Status, Opportunities and Future Challenges. *Journal of Building Engineering*, *44*. https://doi.org/10.1016/j.jobe.2021.103299

Acciarini, C., Cappa, F., Boccardelli, P., & Oriani, R. (2023). How can organizations leverage big data to innovate their business models? A systematic literature review. *Technovation*, *123*, 102713. https://doi.org/10.1016/j.technovation.2023.102713

Adel, K., Elhakeem, A., & Marzouk, M. (2023). Decentralized System for Construction Projects Data Management Using Blockchain and Ipfs. *Journal of Civil Engineering and Management*, *29*(4), 342–359. https://doi.org/10.3846/jcem.2023.18646

Ahmed, V., Tezel, A., Aziz, Z., & Sibley, M. (2017). The future of Big Data in facilities management: opportunities and challenges. *Facilities*, *35*(13–14), 725–745. https://doi.org/10.1108/F-06-2016-0064

Akinosho, T. D., Oyedele, L. O., Bilal, M., Ajayi, A. O., Delgado, M. D., Akinade, O. O., & Ahmed, A. A. (2020). Deep learning in the construction industry: A review of present status and future innovations. *Journal of Building Engineering*, *32*. https://doi.org/10.1016/j.jobe.2020.101827

Alfaro, E., Bressan, M., Girardin, F., Murillo, J., Someh, I., & Wixom, B. H. (2019). BBVA's data monetization journey. *MIS Quarterly Executive*, *18*(2), 111–128. https://doi.org/10.17705/2msqe.00011

Arcadis. (2024, March 26). *Construction cost Handbook*. Arcadis. https://www.arcadis.com/en/knowledge-hub/perspectives/asia/research-and-publications/construction-cost-handbook

Arent van't Spijker. (2014). *The New Oil: Using Innovative Business Models to turn Data Into Profit* (1st ed.). Technics Publications.

Ayodele, T. O., & Kajimo-Shakantu, K. (2022). Challenges and drivers to data sharing among stakeholders in the South African construction industry. *Journal of Engineering, Design and Technology*, *20*(6), 1698–1715. https://doi.org/10.1108/JEDT-02-2021-0074

Bilal, M., Oyedele, L. O., Akinade, O. O., Ajayi, S. O., Alaka, H. A., Owolabi, H. A., Qadir, J., Pasha, M., & Bello, S. A. (2016). Big data architecture for construction waste analytics (CWA): A conceptual framework. *Journal of Building Engineering*, *6*, 144–156. https://doi.org/10.1016/j.jobe.2016.03.002

Bilal, M., Oyedele, L. O., Kusimo, H. O., Owolabi, H. A., Akanbi, L. A., Ajayi, A. O., Akinade, O. O., & Davila Delgado, J. M. (2019). Investigating profitability performance of construction projects using big data: A project analytics approach. *Journal of Building Engineering*, *26*. https://doi.org/10.1016/j.jobe.2019.100850

Bilal, M., Oyedele, L. O., Qadir, J., Munir, K., Ajayi, S. O., Akinade, O. O., Owolabi, H. A., Alaka, H. A., & Pasha, M. (2016). Big Data in the construction industry: A review of present status, opportunities, and future trends. In *Advanced Engineering Informatics* (Vol. 30, Issue 3, pp. 500–521). Elsevier Ltd. https://doi.org/10.1016/j.aei.2016.07.001

Bohé, A., Hong, M., Macdonald, C., & Paice, N. (2013). *Data Monetization in the Age of Big Data*. https://www.accenture.com/in-en/case-studies/communications-media/manzoni

Boyes, H. (2015). *Security, Privacy, and the Built Environment*.

Braun, T., Fung, B. C. M., Iqbal, F., & Shah, B. (2018). Security and privacy challenges in smart cities. *Sustainable Cities and Society*, *39*, 499–507. https://doi.org/10.1016/j.scs.2018.02.039

Building Cost Information Service. (2024, March 26). *Unlocking Data*. Building Cost Information Service. https://bcis.co.uk/

Building Cost Information Services Malaya. (2024, March 26). *N3C*. Building Cost Information Services Malaya. https://n3c.cidb.gov.my/n3c/index.php

Chaurasia, S., & Verma, S. (2020). Strategic Determinants of Big Data Analytics in the AEC Sector: A Multi-Perspective Framework. *Construction Economics and Building*, *20*(4), 63–81. https://doi.org/doi.org/10.5130/AJCEB.v20i4.6649

Construction Industry Development Board. (2020). *Construction 4.0 Strategic Plan (2021-2025) Next Revolution of the Malaysian Construction Industry*.

Dixon, T., Wetering, J. van de, Sexton, M., Lu, S.-L., Williams, D., Duman, D. U., & Chen, X. (2017). *Smart Cities, Big Data and the Built Environment: What's Required?* www.rics.org

Domnina, S. V., Savoskina, E. V., & Shekhova, N. V. (2016). On Innovative Decisions in the Investment-construction Cycle. *Procedia Engineering*, *153*, 741–746. https://doi.org/10.1016/j.proeng.2016.08.236

Faroukhi, A. Z., Alaoui, I. El, Gahi, Y., & Amine, A. (2020). An Adaptable Big Data Value Chain Framework for End-to-End Big Data Monetization. *Big Data and Cognitive Computing*, *4*(4), 1–27. https://doi.org/10.3390/bdcc4040034

Faroukhi, A. Z., El Alaoui, I., Gahi, Y., & Amine, A. (2020). Big data monetization throughout Big Data Value Chain: a comprehensive review. *Journal of Big Data*, *7*(1). https://doi.org/10.1186/s40537-019-0281-5

Fazeli, A., Dashti, M. S., Jalaei, F., & Khanzadi, M. (2021). An integrated BIM-based approach for cost estimation in construction projects. *Engineering, Construction and Architectural Management*, *28*(9), 2828–2854. https://doi.org/10.1108/ECAM-01-2020-0027

Gad, G. M., & Shane, J. S. (2014). Trust in the Construction Industry: A Literature Review. *Construction Research Congress 2014*, 2136–2145. https://doi.org/10.1061/9780784413517.217

Gbadamosi, A. Q., Oyedele, L., Mahamadu, A. M., Kusimo, H., Bilal, M., Davila Delgado, J. M., & Muhammed-Yakubu, N. (2020). Big data for Design Options Repository: Towards a DFMA approach for offsite construction. *Automation in Construction*, *120*. https://doi.org/10.1016/j.autcon.2020.103388

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems*, *27*(1), 101–113. https://doi.org/10.1016/j.jsis.2017.10.001

Ghorbany, S., Noorzai, E., & Yousefi, S. (2023). BIM-based solution to enhance the performance of public-private partnership construction projects using copula bayesian network. *Expert Systems with Applications*, *216*. https://doi.org/10.1016/j.eswa.2023.119501

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

Hanafizadeh, P., & Harati Nik, M. R. (2020). Configuration of Data Monetization: A Review of Literature with Thematic Analysis. *Global Journal of Flexible Systems Management*, *21*(1), 17–34. https://doi.org/10.1007/s40171-019-00228-3

Hartmann, P. M., Zaki, M., Feldmann, N., & Neely, A. (2016). Capturing value from big data – a taxonomy of data-driven business models used by start-up firms. *International Journal of Operations & Production Management*, *36*(10), 1382–1406. https://doi.org/10.1108/IJOPM-02-2014-0098

Hashim, M. A., Che Ibrahim, C. K. I., Jaafar, N. A. L., Kordi, N. E., Haron, A. T., & Umeokafor, N. (2024). Building data driven culture for digital competitiveness in construction industry: a theoretical exploration. *International Journal of Construction Management*, 1–13. https://doi.org/10.1080/15623599.2024.2322237

Huang, Y., Shi, Q., Zuo, J., Pena-Mora, F., & Chen, J. (2021). Research Status and Challenges of Data-Driven Construction Project Management in the Big Data Context. *Advances in Civil Engineering*, *2021*. https://doi.org/10.1155/2021/6674980

Inoua, S. M., & Smith, V. L. (2020). *The Classical Theory of Supply and Demand* (ESI Working Paper 20-11).

Ismail, S. A., Bandi, S., & Maaz, Z. N. (2018). An Appraisal into the Potential Application of Big Data in the Construction Industry. *International Journal of Built Environment and Sustainability*, *5*(2). https://doi.org/10.11113/ijbes.v5.n2.274

Jiang, J., & Gallupe, R. B. (2015). Environmental Scanning and Business Insight Capability: The Role of Business Analytics and Knowledge Integration. *Twenty-First Americas Conference on Information Systems*, 1–28.

Khalfan, M. M. A., McDermott, P., & Swan, W. (2007). Building trust in construction projects. *Supply Chain Management: An International Journal*, *12*(6), 385–391. https://doi.org/10.1108/13598540710826308

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

Koseleva, N., & Ropaite, G. (2017). Big Data in Building Energy Efficiency: Understanding of Big Data and Main Challenges. *Procedia Engineering*, *172*, 544–549. https://doi.org/10.1016/j.proeng.2017.02.064

Laitila, M. (2017). *Data monetization: Utilizing data as an asset to generate new revenues for firms*. Aalto University.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2010, December 21). *Big Data, Analytics and the Path From Insights to Value*. MIT Sloan Management Review. https://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value/

Lewis, A., & McKone, D. (2016, May 10). *So Many M&A Deals Fail Because Companies Overlook This Simple Strategy*. Harvard Business Review.

Liu, C.-H., & Chen, C.-L. (2015). A Review Of Data Monetization: Strategic Use Of Big Data. *15th International Conference on Electronic Business*, 12–18. https://aisel.aisnet.org/iceb2015

Lu, W., Webster, C., Peng, Y., Chen, X., & Chen, K. (2018). Big Data in Construction Waste Management: Prospects and Challenges. *Detritus*, *4*(December), 129–139. https://doi.org/10.31025/2611-4135/2018.13737

Lu, Y., & Zhang, J. (2021). Bibliometric analysis and critical review of the research on big data in the construction industry. *Engineering, Construction and Architectural Management*. https://doi.org/10.1108/ECAM-01-2021-0005

Maaz, Z. N., Bandi, S., & Amirudin, R. (2018). A contextual parsing of big data values to quantity surveyors. *International Journal Of Built Environment And Sustainability*, *5*(3), 241–250.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). *Big data: The next frontier for innovation, competition, and productivity*. www.mckinsey.com/mgi.

Mauri, M. (2022). *Information Visualization for the Construction Industry* (pp. 185–206). https://doi.org/10.1007/978-3-030-82430-3_8

Mehta, S., Dawande, M., Janakiraman, G., & Mookerjee, V. (2019). How to Sell a Dataset? Pricing Policies for Data Monetization. *Proceedings of the 2019 ACM Conference on Economics and Computation*, 679–679. https://doi.org/10.1145/3328526.3329587

Mehta, S., Dawande, M., Janakiraman, G., & Mookerjee, V. (2022). An Approximation Scheme for Data Monetization. *Production and Operations Management*, *31*(6), 2412–2428. https://doi.org/10.1111/poms.13676

Mendoza, R. M. (2023). Project Management Skills, People Management Skills, and Operational Excellence of Construction Project Managers in Private Construction Management Services. *International Journal of Social Science and Education Research Studies*, *03*(06), 1019–1038. https://doi.org/10.55677/ijssers/v03i6y2023-08

Meng, Q., Peng, Q., Li, Z., & Hu, X. (2022). Big Data Technology in Construction Safety Management: Application Status, Trend and Challenge. *Buildings*, *12*(533). https://doi.org/https://doi.org/10.3390/ buildings12050533

Ministry of Works Malaysia. (2024, March 26). *KKR Publications*. Ministry of Works Malaysia. https://www.kkr.gov.my/en/gallery/list-kkr-publications?page=0

Moro-Visconti, R. (2020). Big Data Valuation. In *The Valuation of Digital Intangibles* (pp. 345–360). Springer International Publishing.

Moura, J., & Serrão, C. (2015). Security and Privacy Issues of Big Data. In *Handbook of Research on Trends and Future Directions in Big Data and Web Intelligence* (pp. 20–52). IGI Global.

Najjar, M. S., & Kettinger, W. J. (2013). Data Monetization: Lessons from a Retailer's Journey. *MIS Quarterly Executive*, *12*(4), 213–225.

Nash, S., Chinyio, E., Gameson, R., & Suresh, S. (2010). The Dynamism of Stakeholders' Power in Construction Projects. *Proceeding 26th Annual ARCOM Conference*, 471–480.

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

O'brien, W., London, K., & Vrijhoef, R. (2004). Construction supply chain modeling: a research review and interdisciplinary agenda. ICFAI Journal of Operations Management, 3(3), 64–84. https://hdl.handle.net/10536/DRO/DU:30020890

Ofulue, J., & Benyoucef, M. (2022). Data monetization: insights from a technology-enabled literature review and research agenda. *Management Review Quarterly*. https://doi.org/10.1007/s11301-022-00309-1

Owolabi, H. A., Bilal, M., Oyedele, L. O., Alaka, H. A., Ajayi, S. O., & Akinade, O. O. (2020). Predicting Completion Risk in PPP Projects Using Big Data Analytics. *IEEE Transactions on Engineering Management*, *67*(2), 430–453. https://doi.org/10.1109/TEM.2018.2876321

Parvinen, P., Pöyry, E., Gustafsson, R., Laitila, M., & Rossi, M. (2020). Advancing data monetization and the creation of data-based business models. *Communications of the Association for Information Systems*, *47*, 25–49. https://doi.org/10.17705/1CAIS.04702

Patel, T., & Patel, V. (2020). Data Privacy in Construction Industry by Privacy-Preserving Data Mining (PPDM) Approach. *Asian Journal of Civil Engineering*, *21*(3), 505–515. https://doi.org/10.1007/s42107-020-00225-3

Preidel, C., Borrmann, A., Oberender, C., & Tretheway, M. (2016). Seamless integration of common data environment access into BIM authoring applications: The BIM integration framework. In S. Christodoulou & R. Scherer (Eds.), *eWork and eBusiness in Architecture, Engineering and Construction: ECPPM 2016* (1st Edition). CRC Press.

Public Works Department Malaysia. (2024, March 26). *Technical Documents*. Public Works Department Malaysia. https://www.jkr.gov.my/my/page/dokumen-teknikal-0

Qian, X. (Alice), & Papadonikolaki, E. (2020). Shifting trust in construction supply chains through blockchain technology. *Engineering, Construction and Architectural Management*, *28*(2), 584–602. https://doi.org/10.1108/ECAM-12-2019-0676

Raddats, C., Naik, P., & Ziaee Bigdeli, A. (2022). Creating value in servitization through digital service innovations. *Industrial Marketing Management*, *104*, 1–13. https://doi.org/10.1016/j.indmarman.2022.04.002

Radl, J., & Kaiser, J. (2019). Benefits of Implementation of Common Data Environment (CDE) into Construction Projects. *IOP Conference Series: Materials Science and Engineering* , 1–4. https://doi.org/doi:10.1088/1757-899X/471/2/022021

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

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

Reyes-Veras, P. F., Renukappa, S., Suresh, S., & Algahtani, K. (2022). *Strategies for Implementing Big Data Concept in the Construction Industry of the Dominican Republic*. https://wlv.openrepository.com/handle/2436/624487

Ritala, P., Keränen, J., Fishburn, J., & Ruokonen, M. (2024). Selling and monetizing data in B2B markets: Four data-driven value propositions. *Technovation*, *130*. https://doi.org/10.1016/j.technovation.2023.102935

Sawhney, A., & Knight, A. (2023). *Digitalisation in Construction Report 2023*. www.rics.org

Schober, P., & Schwarte, L. A. (2018). Correlation coefficients: Appropriate use and interpretation. *Anesthesia and Analgesia*, *126*(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Shubham Shubham, Saloni Saloni, & Sidra-Tul-Muntaha. (2023). Optimizing construction processes and improving building performance through data engineering and computation. *World Journal of Advanced Research and Reviews*, *18*(1), 390–398. https://doi.org/10.30574/wjarr.2023.18.1.0614

Tan, Y. J., Maaz, Z. N., Bandi, S., & Palis, P. A. (2023). *Common Data Environment: Bridging the Digital Data Sharing Gap Among Construction Organizations* (pp. 333–342). https://doi.org/10.1007/978-3-031-25274-7_27

Tanga, O., Akinradewo, O., Aigbavboa, C., Oke, A., & Adekunle, S. (2022). Data Management Risks: A Bane of Construction Project Performance. *Sustainability (Switzerland)*, *14*(19). https://doi.org/10.3390/su141912793

Taylan, O., Kabli, M. R., Porcel, C., & Herrera-Viedma, E. (2017). Contractor Selection for Construction Projects Using Consensus Tools and Big Data. *International Journal of Fuzzy Systems*.

Teece, D. J., & Linden, G. (2017). Business models, value capture, and the digital enterprise. *Journal of Organization Design*, *6*(1), 8. https://doi.org/10.1186/s41469-017-0018-x

Thomas, L. D. W., & Leiponen, A. (2016). Big Data Commercialization. *IEEE Engineering Management Review*, *44*(2), 74–90. https://doi.org/10.1109/EMR.2016.2568798

Vaske, J. J., Beaman, J., & Sponarski, C. C. (2017). Rethinking Internal Consistency in Cronbach's Alpha. *Leisure Sciences*, *39*(2), 163–173. https://doi.org/10.1080/01490400.2015.1127189

Wixom, B. H. (2014, August 21). *Cashing in Your Data*. MIT Centre for Information Systems Research. https://cisr.mit.edu/publication/2014_0801_DataMonetization_Wixom

Wixom, B. H., & Ross, J. W. (2018). How to Monetize Your Data. In *How to Go Digital* (pp. 39–48). The MIT Press. https://doi.org/10.7551/mitpress/11633.003.0009

Woerner, S. L., & Wixom, B. H. (2015). Big data: Extending the business strategy toolbox. *Journal of Information Technology*, *30*(1), 60–62. https://doi.org/10.1057/jit.2014.31

Woroch, R., & Strobel, G. (2022). Show me the Money: How to monetize data in data-driven business models? *Wirtschaftsinformatik 2022 Proceedings*, 1–16. https://aisel.aisnet.org/wi2022

Wu, L., & Abourizk, S. M. (2021). Towards Construction ' S Digital Future : A Roadmap For Enhancing Csce 2021 Annual Conference Towards Construction ' S Digital Future : A Roadmap For. *CSCE 2021 Annual Conference Inspired*, *May*. https://doi.org/10.13140/RG.2.2.29564.67205

Wu, Z., Chen, C., Cai, Y., Lu, C., Wang, H., & Yu, T. (2019). BIM-Based Visualization Research in the Construction Industry: A Network Analysis. *International Journal of Environmental Research and Public Health*, *16*(18), 3473. https://doi.org/10.3390/ijerph16183473

Yuan, Z., Yu, X., Jiang, Y., Sun, J., Liu, Z., & Li, B. (2024). Current status and governance of data assets monetization in the global maritime industry: A comparative study of the United States, Europe, and China. *Ocean and Coastal Management*, *251*. https://doi.org/10.1016/j.ocecoaman.2024.107078

Zhang, X., Yue, W. T., Yu, Y., & Zhang, X. (2023). How to monetize data: An economic analysis of data monetization strategies under competition. *Decision Support Systems*, *173*. https://doi.org/10.1016/j.dss.2023.114012