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Critical Factors Influencing Adoption of Blockchain-Enabled Smart Contracts in Construction Projects

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ABSTRACT

Construction projects are premised upon contractual arrangements, and contracts constitute the basis of their success. A contract enables execution of work and transfer of payments, tracking of key performance indicators and facilitation of collaboration between project stakeholders. Historically, construction projects have faced critical challenges due to poor alignment between clients' expectations, contract terms and contractor performance. The advent of advanced digital technologies under the concept of Industry 4.0 has the potential to benefit construction projects through application of blockchain-enabled smart contracts. However, the adoption of smart contracts in construction projects is at its early stage and what factors will influence its adoption remain unclear. Therefore, this study seeks to explore and establish the critical factors influencing adoption of smart contracts in construction contractual arrangements. Drawing on an international questionnaire survey of experienced construction practitioners with involvement in smart contract initiatives and activities, the results obtained from descriptive statistics and fuzzy set-based analysis show that trialability, relative advantage, competitive advantage and compatibility of smart contracts are the important predictors of their adoption. The findings suggest that practitioners share a view that technological characteristics of blockchain-enabled smart contracts are critical to its adoption, regarding the technology's perceived practicality in improving effectiveness and efficiency of construction projects. This study contributes to technology diffusion research in construction and highlights drivers that require practitioners' and

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industry leaders' attention in order to ensure successful adoption of smart contracts for cost-effective delivery of construction projects.

Keywords: Smart contracts; Blockchain technology; Construction projects; Construction industry

INTRODUCTION

The construction industry is a primary driver of economic growth and social development, ensuring the delivery of critical infrastructures for other sectors, creation of jobs and contribution to national gross domestic product (GDP). For example, construction contributes about 6% and 8% to UK's and Australia's GDP, respectively (Pervez 2021; Hook 2019). Globally, McKinsey (2017) estimated that around US$10 trillion is expended on construction products and services annually. However, the construction industry has long been confronted with several challenges that hinder its effective performance, including poor productivity (McKinsey 2017), poor payment practices and associated cash flow difficulties and insolvencies (Peters et al. 2019; Collins 2012), contractual disputes and litigations (Carmichael 2002), and lack of trust and transparency (Edwards and Bowen 2003). Historically, productivity in construction has lagged behind the manufacturing, retail and agriculture industries, with an estimated global construction productivity gap of US$1.6 trillion (McKinsey 2017). According to McKinsey Global Institute, traditional contracts remain detrimental to increased productivity in construction; efficient contracting practices can reduce cost by 6–7% and raise productivity by 8–10% (McKinsey 2017).

Uncertainty in payments represents another well documented major challenge facing construction projects (Collins 2012; Peters et al. 2019; PwC 2019). Late or non-payments result from clients' unwillingness or inability to pay, or disputes over amounts due (Li et al. 2019). This creates adverse impacts on projects, including cost and time slippages, project failures, cash flow difficulties and mistrust (Collins 2012; Manu et al. 2015; Duryez and Hosseini 2019). An inquiry into insolvencies in New South Wales' (Australia) construction industry revealed non-payments or payments withheld as the primary cause (Collins 2012). Also, PwC's (2019) survey of SMEs revealed that 77% of companies had cash flow difficulties resulting from late payments and that required substantial investment of resources and time to chase payments.

Construction disputes are widespread with dire consequences on projects and stakeholders. The industry is highly fragmented and characterised by adversarial, rather than collaborative, relationships (Carmichael 2002). A primary cause of construction disputes has been linked to poor payment practices and the resultant cash flow problems (Collins 2012; Peters et al. 2019). In its '*Global Construction Disputes'* report, Arcadis (2020) observed that the global average cost of disputes is estimated at US$30.7 million, and the average dispute resolution time is 15 months. The Middle East recorded the highest average cost of disputes of US$62 million and North America saw the highest average length of disputes (17.6 months). The report highlights collaboration among project stakeholders as a strategy for disputes avoidance, mitigation and resolution. Unfortunately, a collaborative culture is lacking in the construction industry, which is a contributor to failed projects (De Schepper et al. 2014).

As an efficient way to address the above challenges and to deliver effective construction projects, digital technologies are receiving attention from researchers, practitioners and industry leaders (Penzes et al. 2018; Li et al. 2019). Blockchain and its innovations, such as blockchain-based smart contracts (or smart contracts), are seen as an innovative technology with a potential solution to the foregoing challenges (Hamledari and Fischer 2021; Li et al. 2019; Yang et al. 2020), by making construction projects transparent, accountable and collaborative (Penzes et al. 2018; EY 2018). Administration of smart contracts can significantly benefit construction projects, and several opportunities exist to leverage this technology in the construction industry. Based on its innate characteristics of *immutable*, *secure and traceable*, smart contracts offer a collaborative working environment between clients, contractors, subcontracts, suppliers, and consultants (EY 2018). Such collaborative working improves trust, reduces disputes and provides alignment between contracting parties.

Smart contract technology challenges the contractual model of the highly fragmented construction industry (Arup 2019). Construction projects are procured using traditional contracts which are characterised by intensive documentation and information. This renders some of the contractual processes, such as preparation of interim payment applications, time-consuming, unsecure and frequently erroneous. Blockchain-based smart contracts could help to automate contractual transactions and eliminate paper-based traditional contracts (Hamledari and Fischer 2021) which are easy to forge and take longer to move between contracting parties, making the contractual processes efficient and secure (Ream et al. 2016).

For construction projects, a key area of application of smart contracts is automation of transactions and payments (Hamledari and Fischer 2021; Cardeira 2016). Blockchain-based smart contracts can be designed to automate transactions between contracting parties and automatically effect partial or full payments to contractors, subcontractors and suppliers upon completion of work. Here, contract conditions and schedules of payment are coded into smart contracts upfront (Arup 2019), which execute themselves without third-party intermediaries through automated protocols (Hargaden et al. 2019; Nawari and Ravindran 2019). Automated payment transactions are critical to addressing the problems of late or non-payments and negative cash flow.

Linked to payments automation is improved cash flow through execution of blockchain-enabled smart contracts. This development is expected to be a significant step forward for the construction industry which is frequently cash poor. Smart contracts can be designed to run on the blockchain to manage and monitor construction progress with the advantage of managing cash flow (Hunhevicz 2019). The extent and consequences of cash flow problems was perhaps exemplified by the failure of UK's Carillion Plc. (second largest construction and facilities management company) in January 2018 and further highlights the need for smart contract technology. Carillion suffered late payments and was in debt of £1.5 billion (Thomas 2018). Given Carillion's extended 120-day payment period (Li et al. 2020), the effect of its collapse was felt throughout its supply chains. Blockchain presents a promise to solve such supply chain problems; funds are held centrally on a decentralised blockchain system and authorised following completion and verification of work (Arup 2019). On a construction project, this would help to avoid or reduce intermediaries but also prevent clients from withholding payments to contractors and contractors holding back payments to subcontractors, with the benefit of improved cash flow (Arup 2019).

Despite the foregoing potential of and growing interest in blockchain-based smart contracts, there are limited applications of the technology in administering construction projects. And due to the relative immaturity of smart contracts in construction previous scholarly work that has investigated adoption and implementation at project level remains scant. Specifically, what factors will influence smart contract adoption in construction projects remain unclear. This gap in the current literature is a barrier that further hampers a wider adoption of smart contracts in construction projects and the industry. Also, given the construction industry's inability or reluctance to embrace innovative technologies (Nikas et al. 2007; Merschbrock 2012) previous studies on other technologies (e.g., BIM) explore factors and external pressures exerting influences on their adoption (Ahuja et al. 2009; Cao et al. 2014; Pan and Pan 2021), as a means to incentivise industry stakeholders towards acceptance and adoption of technological innovations. Against this backdrop, it is therefore valuable and timely to investigate the critical factors exerting influences on adoption of smart contracts based on construction practitioners' perceptions. According to Cao et al. (2014), a project constitutes the fundamental unit of construction and the decision adopt a technology is made at the project level. Therefore, this study considers the adoption of smart contracts at the construction project level.

This research draws on international construction professionals with experience and interests in smart contracts initiatives to provide a global perspective on factors influencing their adoption. This study extends the scholarly work on technology diffusion in construction and highlights the primary drivers for greater adoption of blockchain-enabled smart contracts construction projects. It is the first empirical work to explore smart contracts adoption at construction project-level.

LITERATURE REVIEW

Blockchain Technology

In its report, Arup (2019) noted that striping the hype around blockchain, the technology possesses unique characteristics capable of solving many of the omnipresent challenges plaguing the construction industry. Blockchain is a data storage method; it is a shared digital ledger that enables the recording of several transactions as well as tracking of tangible, intangible and digital assets in a network. These assets (e.g., land, house or copyrights) are tracked and traded on the blockchain network at low risk and reduced transaction costs (Gupta 2020). Each data block stores a series of transactions together with a cryptographic summary of the preceding block, making the data blocks chained together and consequently the transactions (data) immutable (Hamledari and Fischer 2021).

Blockchain presents an architecture that enables *nodes* (users) in a network to share an updated ledger via a peer-to-peer replication during a transaction, and consensus is therefore reached in peer-to-peer blockchain networks (Narayanan 2016). A blockchain network introduces a censorship-resistant shared ledger of transactions that are efficient and economical because it avoids or minimises the requirement for intermediaries and duplication of effort, and it is less vulnerable as it adopts a decentralised consensus protocol to verify data (Gupta 2020). Therefore, nodes can authenticate and validate transactions. In the Fintech sector, a popular use case of blockchain technology is Bitcoin (Nakamoto 2008) where blockchain provides a platform to record and store Bitcoin transactions (Bart et al. 2017). Ethereum's blockchain (Buterin 2014) comes with a protocol and a built-in Turing-complete language allowing any user to create decentralised applications (DApp) and smart contracts (Buterin 2014) which can be executed on the Ethereum virtual machine (EVM). EVM is a decentralised world computer that makes it impossible to tamper with smart contracts (Hamledari and Fischer 2021).

Blockchain-enabled Smart Contracts

Smart contracts are among the highly disruptive and critical blockchain technology-enabled innovations (Arup 2017). The notion of a smart contract was introduced in 1994 by a legal scholar and a computer scientist, Nick Szabo (Szabo 1994). Szabo defines a smart contract as "a computerised transaction protocol that executes the terms of a contract." The automated transaction protocol seeks to achieve three broad objectives: to satisfy terms of contractual agreements, reduce both malevolent and accidental errors, and reduce the requirement for intermediaries in enforcing a contract. In other words, a smart contract is a digital computer code (or a programmable contract) that eliminates trusted third parties and self-executes its terms upon satisfaction of pre-set conditions; the code is linked to digital currencies (e.g., ether, bitcoin) as the representation or payment of an asset(s) (Arup 2017; Yang et al. 2020). Szabo (1994) discussed some economic gains of automated contracts which include reduced contractual arbitrations [through automation], low fraud loss, and reduced cost of enforcing contracts and transactions.

Arup (2017) outlined three unique properties for smart contracts viz: first, a smart contract is only recorded on or enabled by blockchain. This allows a smart contract to 'inherit' properties of the blockchain technology, including censorship resistance, immutability, high security, *etc*. Second, the recording and transfer of assets on a blockchain is controlled by a smart contract. Third, a smart contract is executed by a blockchain, and this can only be changed through a consensus by users. These properties differentiate smart contracts from other computerised systems / software. Today, the advent of blockchain technology and Bitcoin (Nakamoto 2008; Arup 2017) are advancing the concept of smart contracts in many industries including construction. Blockchain-based smart contracts can enable a number of construction processes to be automated, improved and made more efficient (Penzes et al. 2018).

Previous Studies on Smart Contracts in Construction

There is a growing interest from industry and academia on blockchain and smart contracts in the construction industry (Li et al. 2019; Arup 2019). However, there is scant scholarly work on the subject due to the relative immaturity of the smart contract technology (Lauslathi et al. 2017). Pertinent literature within the small body of knowledge includes the work of Yang et al. (2020) who drew on two cases to demonstrate practical applications of public and private blockchain technologies in construction business processes. The authors (*ibid*) demonstrated how a smart contract was implemented for procuring a high-priced equipment for an international construction project and highlighted the ability of smart contracts to eliminate payment delays and disputes and enhance contract administration. Li et al. (2019) provided a review of state of blockchain in the built environment and construction industry and proposed a roadmap for adoption. In appraising use cases, Li et al. emphasised that *regulation and compliance* and *project bank accounts* are potential areas for application of blockchain technology. With its characteristics, a smart contract is capable of automating current manually administered payment principles of a project bank account in public construction projects, thereby eliminating the consequences of late payments, non-payment and insolvencies in the construction industry.

Mason (2017) described BIM as the forerunner of smart contracts where blockchain serves as the platform for running smart contracts and that semi-automation, rather than full automation, of contracts is the possible outcome. This assertion is informed by the current limitations of the technology, complexity of projects with frequent variations and the need for human interventions in managing construction contracts (Gabert and Grönlund 2018). Hence, smart contracts could be more suited for simple transactional activities in construction (Mason 2017). Badi et al. (2021) applied the technology-organisation-environment (TOE) model to examine and identify factors influencing adoption and use intention of smart contracts in the UK construction sector. The TOE framework is useful at examining the key influences for adopting technologies within firms, with a focus on technological, organisational, and environmental considerations (Oliveira and Martins 2010). Badi et al.'s (2021) study contributes to understanding of construction organisations' attitudes and perceptions toward smart contracts use; its major limitation, however, is the focus on the UK's construction sector. Given the global interest in smart contracts, it is imperative to explore what global influences are driving adoption and use of smart contracts.

In another study, Hamledari and Fischer (2021) explored the use of blockchain-based smart contracts in automation of interim payments in construction projects, as a means to resolve the inefficient workflows and time-consuming document processing associated with traditional payment practices. Their study presented a use case to illustrate smart contract-based payment processes with an unmanned aerial vehicle-based progress monitoring. As noted earlier, blockchain-based automation of progress payments will benefit project stakeholders through reduced inefficiencies, contractual disputes and opportunity for fraud and corrupt transactions by providing a 'single source of truth for projects' (Zhong-Brisbois 2019; Hamledari and Fischer 2021). Progress payments automation could also reduce costs by minimising or avoiding multiple intermediaries.

The above literature review evidence that smart contract technology can mitigate some of the pertinent problems plaguing construction projects such as inefficient payment practices, high incidence of disputes, and poor contract administration. The literature review also shows that potential areas of application of smart contracts include regulation and compliance, and project bank accounts. Also, it is clear that smart contract has a significant role to play in payments processing and security in construction projects. The current scholarly work is limited to possible use cases and benefits of the smart contract technology.

Prior Studies on Adoption of Digital Technologies in Construction

Construction research continues to explore adoption of various digital technologies in its attempt to address the challenges plaguing construction projects, organisations and the industry. Nikas et al. (2006) examined the antecedents and drivers that influence adoption of collaborative information technologies in the construction industry. The results showed that senior management's commitment to employees' training and skills development and increasing size of an organisation are the primary factors affecting intention to adopt collaborative technologies. In studying information, communication and technology (ICT) adoption, Ahuja et al. (2009) reported that technical, managerial and people issues are the primary factors driving adoption of ICTs in building project management in the construction industry. In a related case study of three large construction organisations in Australia, Peansupap and Walker (2005) reported that the important factors influencing adoption of ICT are related to management, individual, technology and workplace environment issues.

Lee et al. (2013) proposed a BIM acceptance model from the perspectives of individuals and organisations and reported that perceived usefulness of BIM technology and behavior control (internal and external pressure) directly influence individual's intention to adopt and use BIM. Using the institutional theory, Cao et al. (2014) investigated the effects of the coercive, mimetic and normative isomorphic pressures on adoption of BIM in construction projects. Drawing on survey data from construction projects in China, the study showed that mimetic and coercive pressures have a significant effect on BIM adoption in construction projects while normative pressure indicated no influence. In a similar study carried out in the UK, Howard et al. (2017) surveyed the perceptions of construction practitioners working with BIM to determine the issues impeding proliferation of the technology at the individual level. The authors (*ibid*) observed that performance expectancy does not impact behavioral intention to use BIM, and that individuals using BIM may not necessarily anticipate job performance rewards from using it. From the perspective of building contractors in Hong Kong, Pan and Pan (2021) observed that top management support is the most influential determinant of construction robots adoption. Other important determinants include relative advantage, organisational readiness, competitive pressure, and high costs. Prior literature on technology adoption has focused on ICT, BIM and/or other general digital technologies. Every technology is unique, and its adoption and use is influenced by a different set of factors.

Smart contract is a new digital technology in the construction industry, understanding the important factors that affect its successful adoption in construction projects will enhance its adoption rate and use. However, existing literature has not fully attempted to understand the drivers for acceptance and adoption of smart contracts at construction project level. The diffusion of the smart contract technology will not grow in construction projects unless there exists a body of knowledge providing better understanding among project stakeholders of the primary enablers of smart contracts. The construction industry is a laggard in embracing and adopting innovative technologies (Merschbrock 2012), and therefore, to advance adoption of new technologies has often required research to investigate and establish the factors influencing their adoption (Cao et al. 2014; Hwang et al. 2022). This is also true for smart contracts and a wider acceptance and adoption of the technology will depend on bottom-up efforts from stakeholders at construction projects level. This is because technology adoption decision is made at project level (Cao et al. 2014), thereby driving adoption. In addition, there is a global attention on smart contracts, and therefore, awareness and understanding of the global influences affecting adoption of the technology is imperative for advocates and the international construction industry. Yet, very few studies have investigated what would influence smart contracts adoption in construction projects from the perspective of construction practitioners. The current study contributes to filling this knowledge gap by exploring the influences driving the adoption of smart contracts in construction projects from the perspective of construction practitioners across countries. Specifically, this study identifies and prioritises the critical factors exerting influence on adopting smart contracts.

Multi-Level Fuzzy Synthetic Evaluation (FSE) Method

The fuzzy set theory (Zadeh 1965) is a mathematical logic to represent and manipulate fuzzy terms, such critical, very critical, and extremely critical, and uses grades of membership in sets as opposed to the true or false membership in traditional sets. Fuzzy sets are capable of representing a varying degree of truth values and includes any real number between 0 and 1, and therefore, the value of membership function in a fuzzy set defines the degree to which an object belongs to the set (Tah and Carr 2000).

The fuzzy synthetic evaluation (FSE) is a branch of the fuzzy set theory and uses fuzzy mathematics to model and quantify vague expressions that are present in natural language. These vague, fuzzy expressions are called linguistic variables in a fuzzy set environment (Wei et al. 2010; Xu et al. 2010). In practice, a set of factors are frequently evaluated based on expert judgement of decision-makers (such as survey participants) using linguistic variables such as disagree, agree, and strongly agree. The FSE method provides a mathematical way to define and quantify such fuzzy expressions (Thomas et al. 2006). Kuo and Chen (2006) noted that FSE has attributes for evaluating objects or factors. A comprehensive evaluation is performed on the relevant objects to generate the overall evaluation. In producing an overall evaluation, not only the main factors (or objects) are considered, but the sub-factors which define each principal factor are considered which leads to a multi-level problem which is solved by the multi-level FSE. The multi-level fuzzy model is most useful and suited method for calculating the membership values from the lowest level (sub-factors) to the top level (principal factors) (Wei et al. 2010; Hsiao 1998). For example, in this study, the multi-level fuzzy model is used to calculate the overall evaluation score of each critical factor group (CFG) by first determining the membership values of the sub-critical factors that define each CFG. Hence, the evaluation score of a CFG is obtained through deriving the membership values, and then de-fuzzifying the evaluation fuzzy vector, of the CFG. There are attempts to apply FSE method within construction to evaluate and prioritise factors or objects. Tran et al. (2011) proposed a fuzzy set-based methodology to rank the probability and consequences of manhole collapses. Liu et al. (2013) used the FSE method to assess and rank risks associated with construction drilling projects. Xu et al. (2010) used the FSE method to prioritise and rank-order the risks associated public-private partnership (PPP) projects.

RESEARCH METHODS

To explore the phenomena under investigation, this research largely employed an empirical epistemological lens (Merriam 2009) to analyse primary quantitative data collected from a structured questionnaire survey (Hoxley 2008). To explore and reveal factors that influence smart contracts adoption, an interpretivist philosophical stance (Leitch et al. 2010) was adopted in the literature review sections. This enabled the factors identified from the literature (see below) to be refined and reconstructed to suit the study's aim. A questionnaire survey instrument was then prepared premised upon the factors obtained from the literature review – thus constituting a virtuous knowledge cycle on existing theories contributing towards generating new insight. The research methods and approach are described in the sections below. The overall research framework is presented in Fig. 1.

Insert Fig. 1 around here

Identifying Factors Influencing Smart Contracts Adoption

The list of factors influencing adoption of smart contracts is constructed based on a review of: (a) related academic studies on blockchain and smart technologies (Yang et al. 2020; Hamledari and Fischer 2021; Badi et al. 2021). Given the limited scholarly work on smart contracts, relevant studies were purposively searched on websites of top-ranked construction journals; (b) industry reports on blockchain/smart contracts applications in the construction sector, including publications by construction professional bodies and individuals (Penzes et al. 2018; Cardeira 2016; Ream et al. 2018) and consulting firms (Arup 2017, 2019; EY 2018); and (c) technology acceptance theories and technology diffusion studies in construction (Lee et al. 2013; Cao et al. 2014). The outcome of the review exercise yielded 27 factors that could potentially drive smart contracts adoption in construction projects. The factors were carefully constructed to suit the context of the current study and presented in Table 1.

[Insert Table 1 about here]

Questionnaire Survey

The questionnaire was administered to construction practitioners with experience in and/or working on smart contracts initiatives as well as construction academics and researchers focused on blockchain and smart contract technology applications. The questionnaire was initially designed based on outcome of literature review and subsequently, comments from experienced researchers currently working on this subject. Specifically, these researchers provided comments on the data collection instrument's design, structure, scope, appropriateness, wording and clarity of the constructs. The wording of the smart contracts' adoption factors was informed by Badi et al. (2021), but with changes and refinement to suit the context and purpose of the present study. This approach provides an inbuilt validity to the questionnaire (Howard et al. 2017). A questionnaire survey was used as the primary data collection method because it is anonymous, provides reliable data at minimal cost (Cohen et al. 2007), and captures knowledge and experiences of respondents (Hoxley 2008). Also, the questionnaire survey method is widely utilised by researchers to investigate factors influencing technology adoption in construction (Howard et al. 2017; Lee et al. 2013; Cao et al. 2014). The questionnaire consisted of a five-point rating scale (1 = strongly disagree and 5 = strongly agree) that were used to solicit knowledge and opinions of the survey respondents.

Likert scales are widely used in the construction management and engineering research (e.g., Li et al. 2013; Ameyaw et al. 2017; Murphy et al. 2015; Howard et al. 2017; Cao et al. 2014; Lee et al. 2013; Gunduz and Elsherbeny 2020). Construction researchers use Likert scales when conducting surveys of attitudes and opinions in evaluating objects or factors. Likert scales frequently contain a midpoint word such as 'neutral' (Allen and Seaman 2007; Tsang, 2012) as used in the questionnaire survey for this study. The objective is to provide the respondents with a truly neutral opinion without missing their opinions (Tsang, 2012). The presence of a neutral midpoint can also deter respondents from choosing extreme points (responses) on the Likert scale which may not truly reflect their opinions. Thus, the respondent is not compelled to commit to a particular position, thereby providing the benefit of minimising response bias (Croasmum and Ostrom 2011; Tsang 2012). It is a common practice in the construction management literature to treat ordinal variables in Likert scales as interval variables (Ho et al. 2009; Li et al. 2013; Gunduz and Elsherbeny 2020) and can be analysed using descriptive statistics and other analytical methods such as factor analysis and correlation analysis (Harpe 2015; Brown 2011; Carifio and Perla 2008). In addition, the use of Likert scales involves a consideration of reliability, which should be calculated using the Cronbach's alpha reliability test (Brown 2011). In this study, the Cronbach's alpha value was calculated based on the survey data.

The Likert scale response format was developed with the intention to report means and standard deviations of the adoption factors. Therefore, the basic item-writing considerations (Busch 1993) were observed in developing the questionnaire survey instrument using Likert scales. The item stems used statements on which the survey respondents expressed their agreement with each statement according to their knowledge, understanding and experience of smart contracts. Numbered scales ranging from one to five were used because people are comfortable with and think in terms of degrees (Brown 2011; Carifio and Perla 2008; Hwang et al. 2022; Nunnally 1978). Following the above point, the scale category labels (response choices) are presented to provide the survey respondents with the appearance of equal intervals, using the numbered scales. This is to ensure that the response choices are uniformly ranked, avoiding ambiguity and ensuring that the response choices are interpreted consistently and meaningfully (Nunnally 1978; Busch 1993; Harpe 2015). Hence, Likert-type scales are suitable for this study as they generate information (data) based on the survey respondents' expert opinions and knowledge of the topic being investigated. The Likert scale is effective at ranking objects or factors, given that item stems are clearly constructed, response choices are well labelled and uniformly ranked, multiple response options including a neutral response to enable the survey respondents to judge each item stem in terms of agreement. From the foregoing, the survey data allow for the use of means and standard deviations in order to prioritise and determine factors exerting influence on smart contract adoption. Finally, as recommended by Blaikie (2003), the percentages of the survey response for each scale item are calculated.

Questionnaire Administration and Survey Participants

The questionnaire was distributed to professional construction managers, contract managers and administrators, quantity surveyors, project managers and construction researchers working in public and private sectors and universities/research agencies. A robust ethical protocol governed the administration of this survey instrument, which included providing participants with assurances that all personal details given would remain strictly confidential and would not be divulged nor disseminated without prior written consent; guarantees that data protection policies would oversee the handling and management of data security; and an offer that the results would be made freely available post publication. Cumulatively, these ethical and legal measures enabled informed consent to be secured from survey participants but also protect their data privacy. Because smart contract technology is new and adoption is at its early stages (Lauslahti et al. 2017; Badi et al. 2021), the respondents were targeted and purposively selected. The respondents were carefully and purposefully selected based on the guidelines put forward in the literature (Okoli and Pawlowski 2004; Murphy et al. 2015). Selection criteria were developed to identify relevant skills groups. In this study, the main skills groups targeted were industry practitioners and academics/researchers. The individual participants were selected based on the following selection criteria, with a survey respondent having: a) substantial working experience in the construction industry with a direct involvement in projects, b) current and direct involvement or experience in the adoption process of (new) digital technologies in construction, and c) sound understanding and knowledge of blockchain-based smart contract technology and its applications. These criteria include sub-criteria such as evidence of peer-reviewed publications in academic and practitioner journals and membership of industry professional bodies (Murphy et al. 2015). To ensure quality and reliable responses, persons who satisfied the above criteria were considered and invited to participate in the survey. In addition, the respondents hold senior level positions and have between five and over 20 years working experience in the construction industry and delivery of construction projects. In order to provide a global perspective on the driving factors for smart contracts adoption, the survey participants have industry background/experience from 20 countries (Table 2). The respondents were selected through a combination of strategies; searching through LinkedIn profiles, websites of construction organisations, and industry and academic research publications. A chain-referral (snowball) technique (Parker et al. 2019) was also used to increase number of respondents; initially contacted respondents were asked to share the survey with, or recommend, other knowledgeable practitioners in smart contracts who may be willing to participate in the survey.

Survey responses were secured through a web-based survey system (SurveyMonkey®), with a web link to the questionnaire emailed to the respondents. The survey was also shared on the Co-operative Network for Building Researchers (CNBR) platform and the professional network of Project Management Institute (PMI). Overall, 61 responses were received, but 41 were deemed valid for analysis (Table 2). Obtaining a significant number of responses by e-mail contact is challenging (Stern et al. 2014). Some of the invited respondents declined to participate due to lack of knowledge on smart contracts while others failed to complete the survey. Some e-mails bounced because the individuals have moved companies. Because of the strict participant selection criteria adopted and the fact that smart contract is an emerging area, the number of responses achieved is sufficient for analysis.

[Insert Table 2 about here]

The respondents indicate a mix of professional backgrounds and work in various roles within the construction project management team (or as research consultants to such) viz.: 27% contractors/subcontractors, 36% consulting firms, 27% universities and research institutions, 10% for 'other' category. From Table 2, the respondents are senior construction professionals / practitioners with knowledge of and involvement in blockchain and smart contract initiatives and developments in the construction industry; 22% are quantity surveyors; 17% are project and construction managers; 24% are commercial, contract and programme managers/directors; 24% are researchers; and 12% are 'other' category.

ANALYSES AND RESULTS

Statistical analyses were performed on the survey data using the IBM SPSS Statistics 20 and Microsoft Excel Spreadsheet. The analyses include internal consistency reliability of the scale, descriptive mean scoring, relative significance analysis, standard deviation, normalisation analysis and interrater agreement analysis. Extended analysis was performed using fuzzy set theory, which is implemented to evaluate and establish the most important factors influencing on smart contracts adoption.

Reliability Analysis

The Cronbach's alpha coefficient (α) was computed to determine the internal consistency of the adopted scale. A scale's internal consistency gauges the degree to which the scale's items 'hang together' and whether the scale items measure the same underlying construct (Pallant 2010). The α coefficient ranges between 0 and 1, with a value above 0.7 deemed acceptable in exploratory studies (DeVellis 2003). In this study, the calculated α coefficient is 0.945 which suggests an excellent internal consistency reliability of the scale for the sample (Pallant 2010). In addition, the values in the *Inter-Item Correlation Matrix* are all positive, suggesting that the scale's items measured the same underlying constructs, and therefore, the survey data are reliable for statistical analyses (Cohen et al. 2007).

Critical Driving Factors for Smart Contracts Adoption

The mean scores, relative significance (importance) indices (RSI) and normalised values are calculated to establish the important factors (Xu et al. 2010; Lee et al. 2010; Ameyaw et al. 2017) for smart contracts adoption. This helps to ascertain the critical factors influencing adoption of smart contracts. These statistics help to rank order the driving factors in order to extract the critical factors from the general list of 27 used in the questionnaire survey.

The use of descriptive statistics (mean and standard deviation) for preliminary analysis of the survey data is consistent with Harpe's (2015) recommendation that a numerical response format containing at least five response options can be treated as continuous variables. It was argued that the use of numeric presentation (in Likert-type scales) gives the responses interval characteristic, and therefore, means and standard deviations can be calculated for each scale item. Second, Carifio and Perla (2008) concluded that it is "perfectly appropriate to summarise the ratings generated from Likert scales using means and standard deviations". The authors (*ibid*) considered that Likert scale data are similar to interval scale data, with an insignificant degree of measurement error (Shields et al. 1987). For example, Gunduz and Elsherbeny (2020) calculated the means and standard deviations of contract administration factors affecting construction projects using summative ratings from a Likert scale. Hwang et al. (2022) used means and standard deviations to prioritise and establish the important challenges in the, and effective strategies for promoting, adoption of smart technologies in the construction industry. Third, as reported in Table 3, the distribution of the participants' responses (survey data) show that the participants used the full range of response categories of the response categories for each scale item. This means that (i) the 'shorter' item problem is avoided and (ii) the descriptive analysis will produce meaningful results without missing the true message from the data (Harpe, 2015; Carifio and Perla 2008). Based on the five-point Likert scale, five mean ranges relating to different thresholds are used to capture and interpret the level of agreement among the respondents as: ≥1.50 = "strongly disagree"; 1.51–2.50 = "disagree"; 2.51–3.50 = "neutral"; 3.51–4.50 = "agree"; and ≤4.51 = "strongly agree". Therefore, a driving factor with a mean score of ≤3.51 is considered *'critical'* in this study. The mean scores range between 2.29 and 4.41, with 16 (59%) factors ranging between 3.54 and 4.41. The mean ranges and cut-off criterion have been used by previous studies (Li et al. 2013; Ameyaw et al. 2017; Gunduz and Elsherbeny 2020) to prioritise important factors from a list. The mean scores, standard deviations and rankings of the factors are reported in Table 3. In case of equal mean score, the factor with the lowest standard deviation is ranked higher. In addition to the mean values, the percentages of response in each category of the statements are calculated (Blaikie, 2003) and summarised into disagree, neutral and agree in Table 3. These percentage responses provide the basis for building membership functions using the fuzzy set theory (Table 5) for modeling and ranking the critical factor groups influencing smart contracts adoption.

[Insert Table 3 about here]

The RSI is an alternative method for extracting important factors from a list (Kometa et al. 1995). The method transforms the survey respondents' (numerical) ratings of the factors influencing smart contracts adoption to importance indices to establish the relative ranking of the factors. Kometa et al. (1995) used the RSI technique to determine the relative ranking of the attributes of project delivery success. In this study, a factor prioritisation scale is adopted based on the five-point rating scale as: 0.00≤index<0.43 ("low significance"); 0.43≤index<0.57 ("moderate significance"); 0.57≤index<0.71 ("significant"); 0.71≤index<0.86 ("very significant"); and 0.86≤index<1.00 ("extremely significant"). The use of the factor prioritisation scale is based on Ameyaw et al. (2017). A driving factor with an index ≥0.71 is regarded as significant (important); this approach also yields 16 critical factors influencing smart contracts adoption (Table 3). The last method for establishing the critical driving factors is the normalisation technique (Xu et al. 2010). The calculated normalised values are based on the mean scores and are scaled between 0 and 1. Factors with a value ≥0.50 (Xu et al. 2010) are regarded as critical factors (Table 3).

Overall, the results of the statistical analysis yielded 16 driving factors that are perceived by the expert respondents to influence the decision to adopt smart contracts in construction projects. Among the 16 driving factors, the top five critical factors have mean scores and significance indices ranging between 4.00 and 4.41 and 0.80 and 0.88, respectively. These factors include f-13 ($\bar{x}$ = 4.41), f-11 ($\bar{x}$ = 4.17), f-08 ($\bar{x}$ = 4.12), f-01 ($\bar{x}$ = 4.00) and f-04 ($\bar{x}$ = 4.00). The first two factors (f-13 and f-11) relate to ability and opportunity to try-out smart contracts prior to their adoption by stakeholders in construction projects. This is important, given that every new technology has risks that may not be well understood at early stages of implementation. Blockchain and smart contracts are no exception. Smart contract is a new technology-enabled contracting practice (Lauslahti et al. 2017) and the construction industry is trying to understand the extent of their full potential and how they can be leveraged in construction projects (Penzes et al. 2018). A trial period will provide opportunity to carefully analyse the match between practical industry problems and smart contracts' characteristics (Hamledari and Fischer 2021). This is a prerequisite for successful adoption. The third driver is about boosting transparency in construction projects regarding cost, time and score. Transparency is possible because all transactions, payments and information resources are recorded and automatically shared on the blockchain network. This allows each stakeholder to follow the process and authenticate their records.

Agreement Analysis of the Critical Factors

The inter-rater agreement (IRA) method was used to measure the amount of consensus by the respondents on the ratings of the 16 critical factors influencing smart contracts adoption established above. The IRA method is an alternative and a popular technique for assessing the strength of agreement among group respondents (Brown and Hauenstein 2005). In this study, Brown and Hauenstein's (2005) IRA estimate, a_{WG}, is used to assess the absolute consensus in ratings provided by the survey respondents for each factor (Eq. 1). The a_{WG} estimate has been used in construction studies to measure consensus among survey respondents. For example, Ameyaw et al. (2017) used the a_{WG} estimate to ascertain the level of agreement among practitioners on significance of critical success factors water-based PPP projects. Gunduz and Elsherbeny (2020) applied the a_{WG} estimate to evaluate the strength of agreement construction contract administration factors on project performance. The IRA statistic ranges between -1 and +1 and captures the amount of agreement to the highest possible disagreement. An estimate of 1 represents a perfect agreement among the respondents and vice versa and is interpreted as: 0.00–0.30 = *"lack of agreement;"* 0.31–0.50 = *"weak agreement;"* 0.51–0.70 = *"moderate agreement;"* 0.71–0.90 = *"strong agreement;"* and 0.91–1.00 = *"very strong agreement."* An estimate of 0.71 and above suggests a high degree of consensus.

$$a_{WG(1)} = 1 - \frac{2 * s_x^2}{[(H+L)M - M^2 - (H*L)] * [k/(k-1)]} \qquad [1]$$

where *M* denotes the observed mean score based on respondents' ratings for a given factor, *H* and *L* represents the maximum and minimum values of the Likert scale (5 and 1) respectively, *k* indicates the number of survey respondents, and S_X^2 denotes observed variance on *M*. The IRA results are reported in Table 4, ranging from 0.69 to 0.83 with fifteen factors rated as '*strong agreement*' and one factor rated as *'moderate agreement.'* The results indicate that the respondents' assessment of the factors are not random responses (Ameyaw et al. 2017).

Grouping the Critical Factors

After establishing the 16 critical factors (CFs) from the statistical analyses (see Table 3), they were subject to further analysis using the fuzzy set theory. However, before applying the fuzzy set theory, the 16 CFs are classified into four critical factor groups (CFGs), namely: 1) compatibility; 2) competitive advantage; 3) triability; and 4) relative advantage (see Table 5). This categorisation is based on the attributes (characteristics) of innovations by Rogers (2003) and technology, organisation and environment (TOE) framework by DePietro et al. (1990). For example, compatibility, trialability, and relative advantage are among the five general attributes of innovations Rogers (2003) identified to consistently influence technological innovations adoption. The innovation attributes explain 49% to 87% of the variance in the adoption rate of innovations (Rogers 2003). Similarly, competitive advantage is an environmental factor of the TOE framework that influences successful adoption of technological innovations (Pan and Pan 2021; Lee et al. 2013; Chatterjee et al. 2021). Innovation adoption research has shown that attributes of innovation and the TOE concept influence technological innovation adoption and have been applied to investigate technology adoptions in different disciplines, including construction (e.g., Pan and Pan 2021; Lee et al. 2013). Grouping the 16 CFs into four CFGs based on well-established technology adoption theories/frameworks provides inbuilt reliability to the classification without the need for a statistical classification. As shown in Table 5, each CFG is measured and defined by a number of CFs which together provide a measure of that factor group. Overall, the 16 critical factors capture and explain some of the most important factors facilitating adoption of technology. It is worth noting that adoption of a technology will be driven by a set of factors influenced by characteristics of the technology, industry conditions (Lee et al. 2013). In this study, the 'relative advantage' group has the highest numbers of factors (Table 5), suggesting that adoption of a new technology in construction is significantly influenced the potential benefits it can offer to adopters. The next stage of the analysis involves combing the scores of the CFs of each CFG into one score using the fuzzy set theory in order to rank the CFGs.

Evaluating the Critical Factors and Critical Factor Groups using Fuzzy Set Theory

Having categorised the critical factors into categories into four factor groups (Table 5), the fuzzy set theory (FST) (Zadeh 1965; Hsiao 1998) is used to employed to evaluate and rank the factor groups. The objective is to establish the most important factor groups exerting influence on adoption of smart contracts. The FST is practical at dealing with and overcoming vagueness and subjectivity that characterise traditional questionnaire survey responses using linguistic variables (Ameyaw et al. 2015). The FST has been used in construction research to address practical problems, including risk allocation decision-making (Ameyaw and Chan 2015) and risk assessment and ranking (Ameyaw et al. 2017). Readers may refer to these studies for applications of the FST. Hence, this section presents the relevant definitions and theoretic operations that are used to develop the analysis and ranking methodology outlined below.

The first step in the FST is the representation of fuzzy sets to derive the membership functions. $\boldsymbol{U}$ constitutes a universal set and represents a set of objects represented generically by x, then a fuzzy set $\boldsymbol{A}$ in $\boldsymbol{U}$ can be generated as follows:

$$\boldsymbol{A} = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots + \frac{\mu_A(x_n)}{x_n} \qquad [2]$$

where $\mu_A(x)$ is the grade membership (or membership function), the expressions $\frac{\mu_A(x_i)}{x_i}$ are not fractions but represent the relation between x_i and its grade membership $\mu_A(x_i)$, which ranges from [0,1]. Hence, grade membership of a specific critical factor for smart contract adoption is expressed as:

$$\boldsymbol{A} = \frac{\mu_A(x_1)}{\text{strongly disagree}} + \frac{\mu_A(x_2)}{\text{disagree}} + \cdots + \frac{\mu_A(x_n)}{\text{strongly agree}} \qquad [3]$$

And the grade membership of a critical factor A_i based on above expression is written as:

$$\boldsymbol{A}_i = (\mu_A(x_1),\quad \mu_A(x_2),\quad \dots\quad \mu_A(x_i)), \text{ and } \sum_{i=1}^{n} \mu_A(x_i) = 1 \qquad [4]$$

For example, the membership function of critical factor *f-15* is derived using Eq. [3] and expressed using Eq. [4]:

$$\boldsymbol{A}_{d15} = (0.000 \quad 0.122 \quad 0.293 \quad 0.390 \quad 0.195)$$

Having established the grade membership for each critical factor, the fuzzy relational matrices can be derived. Say ***R*** denotes a fuzzy relation on ***X*** × ***Y***, where ***X*** and ***Y*** have *m* and *n* elements, respectively. Then following from Eq. [4], ***R*** is defined by the relational matrix as follows:

$$\boldsymbol{R} = (x_{ij})_{mn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \qquad [5]$$

Thus, ***R*** is called fuzzy relational matrix and its elements of are given by $x_{ij} = \mu_R(x_i, y_i)$ whose memberships range from [0,1]. Using Eq. [5], the fuzzy relational matrix for *'Competitive advantage (CA)'* is derived:

$$\boldsymbol{R}_{\text{Competitive advantage}} = \begin{bmatrix} 0.000 & 0.122 & 0.293 & 0.390 & 0.195 \\ 0.049 & 0.049 & 0.366 & 0.366 & 0.171 \\ 0.000 & 0.073 & 0.293 & 0.439 & 0.195 \end{bmatrix}$$

The values of the fuzzy relational matrices of all the critical factor groups are presented in Table 5.

The next step is to establish the weightings of the critical factors and consequently the weighting function set of each critical factor group. Using the mean scores, the weightings of the individual critical factors and the critical factor group through the following equation and reported in Table 5:

$$\boldsymbol{w}_i = {M_i}\Big/{\sum_{i=1}^{n} M_i} \qquad [6]$$

where w_i is the weighting of a driving factor i or factor group i; M_i is the means score of driving factor i; $\sum_{i=1}^{n} M_i$ is sum of all mean values of the driving factors of factor groups. The weighting of a factor reflects its importance regarding influencing smart contract adoption and ranges between 0 and 1, with the sum of a weighting function set equals to 1, i.e., $\sum_{i=1}^{m} W_i = 1$ (Hsiao 1998). Hence, the weighting function set of *'Competitive advantage'* factor is given by:

$$\boldsymbol{W}_{\text{Competitive advantage}} = \{w_{d3}, \quad w_{d15}, \quad w_{d23}\} = \{0.342, \quad 0.333, \quad 0.324\} = \sum W = 1$$

Having established the fuzzy relational matrices and the weighting function sets of the factor groups, then the fuzzy synthetic evaluation set, $\boldsymbol{Z}$, of a given factor group is given by:

$$\boldsymbol{Z} = \boldsymbol{W} \circ \boldsymbol{R} = \{z_1, \quad z_2, \quad \cdots, \quad z_m\} \qquad [7]$$

where $\boldsymbol{Z}$ gives grades of membership of a critical factor group; and " $\circ$ " denotes composite operation processed by various fuzzy mathematical functions (Hsiao 1998). Here, the generalised weighted mean method $M(*, +, \beta)$ is used to perform the composite operation in Eq. [7]. The characteristic of this method is that it takes into consideration and preserves the effects of all the individual critical factors, and so, the value of β = 1 (Hsiao 1998). Also, in this study the weightings are normalised ($\sum_{i=1}^{m} W_i = 1$), and therefore the model regresses to addition of real numbers. The $M(*, +, \beta)$ method (Hsiao, 1998) is defined as

$$\boldsymbol{z}_j = \left(\sum_{i=1}^{m} W_i * x_{ij}^{\beta}\right)^{1/\beta}, \; j = 1,2, \dots, n \qquad [8]$$

Using *'Competitive advantage'* as an example, the member functions are obtained as follows:

$$\boldsymbol{Z}_{\text{Competitive advantage}} = \begin{bmatrix} 0.342 \\ 0.333 \\ 0.324 \end{bmatrix} * \begin{bmatrix} 0.000 & 0.122 & 0.293 & 0.390 & 0.195 \\ 0.049 & 0.049 & 0.366 & 0.366 & 0.171 \\ 0.000 & 0.073 & 0.293 & 0.439 & 0.195 \end{bmatrix}$$

$$= (0.016 \quad 0.082 \quad 0.316 \quad 0.399 \quad 0.187)$$

Now, the critical values of each factor group are computed through Eq. (8) using the grade memberships. This process is called defuzzification, which transforms fuzzy memberships into crisp values (Ameyaw and Chan 2015) to ascertain their degree of influence in adopting smart contracts. The criticality values are presented in column 5 of Table 5.

$$\mathbf{Index}_{[\text{factor group i}]} = \boldsymbol{Z}_i * \boldsymbol{E} \qquad [9]$$

where E denotes scale options to measure criticality of the factors or groups. In this study, five scale options are used and interpreted as $e_1 =$ not critical [1], $e_2 =$ slightly critical [2], $e_3 =$ moderately critical [3], $e_4 =$ critical [4], and $e_5 =$ very critical [5]. For example, the index of *'competitive advantage'* is obtained as follows:

$$\textbf{Index}_{[\text{Competitive advantage}]} = (0.016, \quad 0.082, \quad 0.316, \quad 0.399, \quad 0.187) * (1,2,3,4,5) = 3.660$$

The relative indexes of all the CFGs are above 3.51, ranging between 3.54 and 4.30 (Table 5), suggesting that they positively impact decision to adopt smart contracts in construction projects.

DISCUSSION

This study sought to establish the critical factors influencing adoption of blockchain-based smart contracts in construction projects, drawing on the views of construction experts and practitioners. The descriptive analyses yielded 16 critical factors believed to influence smart contracts adoption, which are further grouped into four critical factor groups as: 1) trialability; 2) relative advantage; 3) competitive advantage; and 4) compatibility.

Trialability

Trialability is the first factor group lending support to adoption of smart contracts and comprises of two factors (f-11 and f-13) with a relative criticality index of 4.30 (Table 5). It refers to the extent to which a technological innovation may be experimented with on a limited basis before adoption (Rogers and Shoemaker, 1971). This finding finds support for previous studies that highlight the significant influence of trialability in successful adoption of innovative technologies (Lin and Chen 2012; Rogers 2003; Kendall et al. 2001). Technological innovations that can be tried are adopted more frequently and quickly compared to less trialable ones (Kendall et al. 2001; Tornatzky and Klein 1982). In this study, trialability is highly advocated by the survey respondents, with 98% voting that they would experiment with smart contracts before adoption in practice and 83% in favour of a trial period prior to adoption. In other words, trialability is characterized by *ability to try out* (f-13), and *opportunity to experiment* with (f-11) smart contracts on real projects before adoption. Both factors have been reported to enhance the prospect of successful adoption of innovations (Lin and Chen 2012). Unsurprisingly, both factors were rated highly by the survey respondents, with mean values > 4.00 (Table 3). Indeed, this finding suggests the necessity for a trial period to experiment with smart contracts before practical implementation; the testing period is valuable to identifying potential risks, bugs and failures and addressing them in a safe and secure manner before application in practice. Blockchain applications and smart contract systems are new technologies that will require trial to build trust, collaboration and confidence of project stakeholders (Mason and Escott 2018; Badi et al. 2021). Although numerous studies including this study have observed that trialability characteristic positively influences technology adoption, Badi et al. (2021) found no positive correlation between trialability and smart contracts adoption in the UK construction sector. A possible reason could be that their respondents were not engaged in smart contract activities and had little or no knowledge and understanding of smart contracts, unlike in this study where the respondents are involved in smart contract initiatives.

Relative Advantage

The second factor group influencing smart contracts adoption in construction projects is relative advantage which is measured by nine critical factors (see Table 5). According to Moore and Benbasat (1991), relative advantage refers to the extent to which a technological innovation is perceived as being better than its predecessor. Relative advantage is akin to Davis' (1989) *perceived usefulness* characteristic and is strongly espoused as a fundamental predictor of innovation adoptions (Pan and Pan 2021; Rogers 2003; Lee 2004). Thus, this finding is in parity with previous studies that highlight relative advantage as a key driver of adoption of other technologies (Lee et al. 2015; Chatterjee et al. 2021). For example, Lee et al. (2015) observed that relative advantage significantly affects individual's intention to accept BIM while Chatterjee et al. (2021) reports that relative advantage is positively associated with adoption of artificial intelligence (AI) in the manufacturing industry. The criticality index of 3.88 (Table 5) suggests that practitioners regard blockchain-enabled smart contract technology as an instrument to enhance job performance and that smart contracts are perceived to impact on and enhance efficient delivery of construction projects. From Table 3, the respondents perceive smart contracts to have potential benefits, including maximises transparency in cost, time and scope (78%, $\bar{x}$ = 4.12), facilitates progress payments (76%, $\bar{x}$ = 4.00), provides secured payment transactions (68%, $\bar{x}$ = 4.00) and reduces ambiguities in project scope (78%, $\bar{x}$ = 3.95). In related studies, researchers highlighted potential benefits of smart contracts adoption in construction, including security of payments, automatised payments, reduced disputes, and automated contract formation (Mason and Escott 2018), cultivation of trust and collaboration *by design* and risk mitigation (Hamledari and Fischer 2021). Overall, this finding suggests that working with smart contracts is a rewarding task for practitioners and that smart contract technology is capable of creating benefits in projects – crucial to facilitating smart contracts adoption.

Competitive Advantage

The third factor group influencing adoption of smart contracts in construction projects is competitive advantage, with an adoption index of 3.66. Competitive advantage of a technological innovation is the extent to which the technology provides gains or benefits to (project) organisations (Rogers 2003) and is reported to strongly influence technology adoption across sectors (Pan and Pan 2021; Chatterjee et al. 2021; Badi et al. 2021). As organisations compete to become pioneers in the use of emerging (often digitalised) technologies (such as those inextricably linked to the rapidly expanding Industry 4.0 concept viz: virtual reality, cloud computing, artificial intelligence, *etc*.) to beat the competition, the more the need to adopt new technologies by rival competitors intensifies. In this study, the respondents agree that smart contracts will increase profit levels of organisations on construction projects ($\bar{x}$ = 3.76), provide adopters with a strong competitive advantage ($\bar{x}$ = 3.66), and enables adopters to beat the competition ($\bar{x}$ = 3.56). This finding aligns with Tornatzky and Klein (1982) who provides an argument for a strong positive correlation between an innovative technology's profitability and its adoption in other industries. Comparatively, smart contracts offer advantages over traditional contracts which have been criticised for being time-consuming to prepare, susceptible to forgery and errors and consequently, responsible for late- or non-payment problems in the construction industry (Ream et al. 2016; Hamledari and Fischer 2021). The construction business environment is fiercely competitive, characterised by low margins; for example, the average margin of contractors in the UK is around 1.5% (The Construction Index 2017). Therefore, this finding emphasises smart contracts' capability to enhance effectiveness and efficiency of projects and to automate transactions and payments, resulting in time and cost effectiveness and reduction in payment times with direct benefits to construction supply chains (Hamledari and Fischer 2021). These advantages will considerably influence decisions to adopt smart contracts in construction projects as adopters will have an edge over their competitors in wining work.

Compatibility

Compatibility emerged as the fourth factor group driving smart contracts adoption in construction projects with an index of 3.54. Rogers and Shoemaker (1971) broadly defined compatibility as the extent to which an "innovation is perceived as being consistent with the existing values, past experiences, and needs of [potential adopters]." Technology's compatibility to potential adopters' needs and experiences is found to be positively correlated to technology (Lee et al. 2015; Moore and Benbasat 1991). Compatibility is represented by two important variables in this study: i) compatibility with *values* and *beliefs* of construction practitioners/organisations; and ii) compatibility with current contract management *needs* and *practices* of practitioners/organisations and projects. The first aspect of compatibility of smart contracts suggests a cognitive or normative compatibility (Moore and Benbasat 1991), which means compatibility with what practitioners think about smart contracts. Thus, smart contracts are highly likely to be adopted and implemented if the project stakeholders perceive smart contracts to be compatible with their value and belief systems. This finding is consistent with previous studies on other technologies such as AI and tourism mobile payment (Chatterjee et al. 2021; Peng et al. 2012). The second aspect implies practical compatibility (Moore and Benbasat 1991) of smart contracts, which refers to compatibility with practitioners' job functions and contract management needs. This finding suggests that the survey respondents believe that smart contracts: 1) hold the potential to support job performance of practitioners; 2) are compatible with *values* and *beliefs* of construction practitioners/projects; 3) are congruent with existing contract practices and management systems; and 4) are able to address construction projects' needs. Advocates argue that smart contracts are key to enhancing efficiency of project management and project governance, project collaboration and transparency, accurate execution and monitoring of contract conditions, and solving late- or non-payment issues (Penzes et al. 2018; Cardeira 2016; Arup 2017; Li et al. 2020).

IMPLICATIONS

The findings hold useful implications for construction practitioners and industry leaders interested in the application of blockchain-based smart contracts in projects and the future of contractual practices. This study contributes to the existing body of knowledge on digitalisation/digital technologies under the concept of Industry 4.0 by providing understanding of the critical issues that require consideration during the adoption process of blockchain-based smart contracts. A better understanding of the primary drivers will guide decision-makers to identify appropriate areas of focus when developing industry and policy strategies to promote wider adoption of blockchain-based smart contracts across the construction industry. This has the potential to contribute toward the digitalisation and transformation of the construction industry and its supply chains. Also, the findings reflect the attitude of practitioners in the construction industry where practitioners are reluctant to adopt new/emerging technologies unless they are convinced of the advantages such technologies bring to their business operations and practices. The findings show that *trialability* and *usefulness* of smart contracts are perceived to be the top-rated driving forces for adoption. This provides opportunity to smart contracts proponents to ensure that there are real-world applications of smart contracts in case projects, in order to raise awareness of the real benefits provided by smart contract technology and encourage wider uptake of the technology among construction practitioners and stakeholders. Trials of smart contracts through case projects is also key to identifying and resolving potential problems that may arise during real implementation and even to build trust and confidence in smart contract technology. Further, the findings are valuable to smart contracts advocates, particularly smart contract designers, contract administrators, and project management and legal consultancies that will be interested in providing professional services to construction clients. The *relative advantage* of smart contracts as a determinant for their adoption suggests that smart contracts designers should be able to design contracts that are practical, able to satisfy the business needs of clients and projects, and compatible with existing contract management systems.

CONCLUSIONS

Blockchain-based smart contracts is attracting a growing interest among construction industry leaders and practitioners. Smart contract is an innovative technology to automate construction contract processes and is showing the potential to enhance the performance and efficiency of construction projects by ensuring transparency, accountability and collaborative working. However, given its nature, the construction industry is a laggard in adopting innovative technologies, facing challenges including resistance to change and fragmentation of the industry. This research study explored and established the critical factors exerting influences on construction project-level adoption of smart contracts using international questionnaire survey of construction practitioners. The findings revealed 16 important factors that are perceived to drive smart contracts adoption and the top five critical factors are ability to try out a smart contract, a trial period before smart contract adoption, maximising transparency in project delivery, facilitating payments and reduced payout time, and security of payment in projects. Agreement analysis shows strong consensus among the survey respondents regarding the importance of the critical factors. In descending order of influence based on computed criticality index values, the four critical factor groups driving smart contracts adoption are trialability, relative advantage, competitive advantage, and compatibility. The respondents share a view that relative advantage and trialability characteristics of smart contracts are crucial *vis-à-vis* the technology's perceived practicality in improving effectiveness and efficiency of construction projects and providing opportunity to experiment with smart contracts prior to implementation. Also, the respondents perceive that smart contract technology is compatible with existing contracting practices / systems and therefore has a potential to solve most challenges confronting construction projects. This has the potential to enhance adoptability of smart contracts, as practitioners may not be required to significantly adjust existing contract management systems and practices.

The results should be interpreted with consideration of some limitations. First, the data for the study are based on a relatively small sample size, although this does not invalidate the significance and reliability of the results. Given the immaturity of smart contract technology and with adoption at early stages across the world, this sample comprising of experienced construction practitioners directly involved in smart contract initiatives and research is deemed adequate to provide useful and reliable results. Second, because of the immaturity of smart contracts, the current study provides an assessment of the generic factors based on technology acceptance theories and models considered to influence adoption of smart contract technology in construction projects. Third, the study's results were based on expert responses of construction practitioners from across the world; hence, the current results may vary from those of country-specific studies as a result of social, cultural, legal and political considerations. Despite this limitation, the results provide a universal set of important factors that may be applicable in many countries given the diverse backgrounds of the respondents. This may necessitate future research studies as noted below.

To further understand and promote adoption of smart contracts in the construction industry will warrant future scholarly works. First, future research studies should be undertaken in other countries to establish specific factors influencing smart contracts adoption. Such studies may apply and evaluate the factors established by the current study. Next, future studies may be conducted to identify specific applications of blockchain-based smart contracts for various project stakeholders, and to propose a framework to promote the adoption and implementation of the technology in construction projects. Finally, future studies may explore influences of institutional isomorphism and support of project owners/clients on smart contract adoption. Clients are the sponsors of projects and therefore bring profound influences on project design, construction and technology adoptions (Cao et al. 2014). Future study could incorporate other important influences for smart contract adoption. Results of such studies have the potential to assist in refining strategies for smart contracts adoption.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1 Potential factors influencing smart contracts adoption

Factor ID	Factor	Statement	Reference
f-01	Facilitation of payments and reduction of payout time	A smart contract facilitates (progress) payments and reduces payout time by reducing delays in invoice verification process	Cardeira (2016), EY (2018), Hamledari and Fischer (2020), Mason and Escott (2018)
f-02	Ease of understanding	A smart contract is easy to understand	Chatterjee et al. (2021)
f-03	Generation of increased profits to adopters	The use of smart contracts will allow the generation of higher profits to organisations	Nikas et al. 2007
f-04	Security of payments in projects	A smart contract provides secured payments in construction projects	Hamledari and Fischer (2020)
f-05	Competitive pressure to adopt smart contracts	The organisation has experienced competitive pressure to adopt smart contracts	Nikas et al. (2007)
f-06	Available technological support adoptions	Existing technologies in the organisation support smart contract adoption	Badi et al. (2021), Lee et al. (2015)
f-07	Minimises intermediaries and overall project costs	A smart contract reduces intermediary and overall project costs by highlighting inefficiencies	EY (2018)
f-08	Maximises transparency in project delivery	A smart contract maximises transparency of project cost, time and scope	EY (2018)
f-09	Consistency with the existing values and beliefs of the organisation	A smart contract is consistent with the existing values and beliefs of the organisation	Chatterjee et al. (2021), Badi et al. (2021), Lee et al. (2013)
f-10	Intention to try out a smart contract in a limited scope prior to adoption	The organisation intends to try out a smart contract in a limited scope in its projects, before deciding whether to adopt it in practice	Badi et a. (2021), Moore and Benbasat (1991)
f-11	A trial period before smart contract adoption	A trial period before adopting a smart contract in practice will reduce perceived risks	Badi et al. (2021), Moore and Benbasat (1991)
f-12	Protection of contracting parties from late payments and insolvencies	A smart contract protects contracting parties from late (progress) payments and potential insolvencies	Arup (2019), Arup (2017)
f-13	Ability to try out a smart contract	Ability to try out a smart contract is important in the organisation's decision to adopt it in future projects	Badi et al. (2021), Moore and Benbasat (1991)
f-14	Compatibility with the existing contract management systems and/or contractual processes	A smart contract is easy to integrate with existing contractual processes and/or compatible with the existing contract management systems in the organisation	Lee et al. (2015), Moore and Benbasat (1991)
f-15	A stronger competitive advantage	The use of smart contracts would offer the organisation a stronger competitive advantage	Nikas et al. (2007), Chatterjee et al. (2021)
f-16	Ease of use and manageable	A smart contract is easy to use and is manageable	Lee et al. (2015), Chatterjee et al. (2021), Mason and Escott (2018), Badi et al. (2021)
f-17	Compatibility with the contract management needs of the organisation/projects	A smart contract is compatible with the contract management needs of the organisation/projects	Lee et al. (2015), Badi et al. (2021)
f-18	Transparent and favourable government legislation	Government legislation about smart contracts is transparent and supports / favours the adoption of smart contracts	EY (2018), Neuburger (2017)
f-19	Availability of resources and experienced and skilled IT personnel	The organisation has adequate resources and experienced and skilled IT personnel to support smart contract adoption	Chatterjee et al. (2021)
f-20	Improved trust among contracting parties	A smart contract improves trust among contracting parties via automatic sharing of corrections to time and material databases	Hamledari and Fischer (2021)
f-21	Minimizing ambiguities in the scope of work	A well-designed and implemented smart contract minimizes ambiguities in the scope of work which would help in quick resolution of change orders and claims	EY (2018)
f-22	Understanding of positive effects of smart contracts	The organisation has a clear understanding of the positive effects of smart contracts in construction projects	Moore and Benbasat (1991), Badi et al. (2021)
f-23	Increased ability to outperform the competition	The use of smart contracts would increase the ability of the organisation to outperform the competition	Chatterjee et al. (2021), Badi et al. (2021), Lee et al. (2015)
f-24	Minimising complexity resulting in informed decision-making	A smart contract minimises complexity thereby facilitating informed decision-making in projects	EY (2018)
f-25	Reduced occurrence, and efficient resolution, of disputes	A smart contract reduces the occurrence, and ensures efficient resolution, of disputes among contracting parties	Hamledari and Fischer (2020)
f-26	Provision of legal protection	Organisations or firms are legally protected through smart contracts	Ferreira (2021), Badi et al. (2021),
f-27	Pressured to adopt smart contracts	The organisation's business partners recommend or push for (i.e., pressure) the adoption of smart contracts	Nikas et al. (2007)

Table 2 Profile of survey respondents

Background	Experience	Count	%
Years of industry experience	3–5	13	31.71
	6–10	5	12.20
	11–19	11	26.83
	20+	12	29.27
Professional category	Quantity surveyor	9	21.95
	Proj. / Construction manager	7	17.07
	Commercial, Contract & Programme manager / director	10	24.39
	Academic / researcher	10	24.39
	Other*	5	12.20
Professional membership	RICS	10	24.39
	CIOB &RICS	6	14.63
	ICE	5	12.20
	ASCE	4	9.76
	RIBA	1	2.44
	Other**	15	36.59
Core business of your organisation	Main/sub-contractor	11	26.83
	Professional consultancy	15	36.59
	University / research institution	11	26.83
	Other***	4	9.76
Construction projects involved in	General construction projects	24	58.54
	PFI / PPP projects	10	24.39
	Mix of above	7	17.07
Countries in which respondents practice(d):	Continent	Country/territory	
	Africa	South Africa, Nigeria, Somalia, Ghana, Angola	
	Asia	China, Hong Kong, Cambodia, Indonesia, India, Malaysia, UAE, Jordan	
	Europe	United Kingdom, Spain, Greece, Turkey	
	North America	United States	
	Oceania	Australia, New Zealand	
	Global	Respondents with work experience across multiple (>3) countries	

*Concession analyst, technology consultant, lawyer, PPP consultant.
**Law Society (NSW, Australia), Technical Chamber of Greece, Assoc. of Consulting Engineers (India), WAPPP.
***Development institution, public institution, manufacturer/supplier; No. of countries: 20 + Global

Table 3 Results of factors influencing smart contracts adoption

Factor ID	*Summary of percentage of participants' responses: Disagreement (%) (*strongly disagree + disagree*)	Neutral (%) (*neither agree nor disagree*)	Agreement (%) (*agree + strongly agree*)	Weighted	Relative significance index	Mean score	Standard deviation	Normalised value	Rank
f-13	2.44	0.00	97.56	181	0.88	4.41	0.63	1.00	1
f-11	2.44	14.63	82.93	171	0.83	4.17	0.77	0.87	2
f-08	2.44	19.51	78.05	169	0.82	4.12	0.81	0.84	3
f-01	7.32	17.07	75.61	164	0.80	4.00	0.97	0.77	4
f-04	4.88	26.83	68.29	164	0.80	4.00	0.92	0.77	4
f-21	7.32	14.63	78.05	162	0.79	3.95	0.92	0.75	6
f-07	7.32	24.39	68.29	158	0.77	3.85	0.88	0.69	7
f-20	7.32	24.39	68.29	157	0.77	3.83	0.86	0.68	8
f-12	12.20	24.39	63.41	156	0.76	3.80	1.01	0.67	9
f-03	7.32	29.27	63.41	154	0.75	3.76	0.86	0.64	10
f-25	14.63	24.39	60.98	153	0.75	3.73	1.03	0.63	11
f-15	12.20	29.27	58.54	150	0.73	3.66	0.94	0.59	12
f-23	9.76	36.59	53.66	146	0.71	3.56	1.00	0.53	13
f-24	14.63	34.15	51.22	146	0.71	3.56	0.98	0.53	13
f-09	9.76	36.59	53.66	145	0.71	3.54	0.81	0.52	15
f-17	9.76	34.15	56.10	145	0.71	3.54	0.87	0.52	15
f-10	19.51	26.83	53.66	139	0.68	3.39	1.09	0.44	17
f-26	19.51	39.02	41.46	139	0.68	3.39	1.00	0.44	17
f-02	21.95	34.15	43.90	137	0.67	3.34	1.04	0.41	19
f-22	24.39	26.83	48.78	136	0.66	3.32	1.21	0.40	20
f-16	24.39	43.90	31.71	132	0.64	3.22	0.99	0.35	21
f-18	26.83	43.90	29.27	127	0.62	3.10	1.04	0.28	22
f-14	36.59	34.15	29.27	121	0.59	2.95	1.09	0.20	23
f-19	46.34	19.51	34.15	118	0.58	2.88	1.19	0.16	24
f-06	43.90	24.39	31.71	116	0.57	2.83	1.22	0.13	25
f-27	43.90	29.27	26.83	114	0.56	2.78	1.13	0.10	26
f-05	48.78	29.27	21.95	106	0.52	2.59	1.26	0.00	27

*Participant opinions are measured using a five-point scale: 1 = Strongly Disagree; 2 = Disagree; 3 = Neither Agree nor Disagree; 4 = Agree; 5 = Strongly Agree. The percentage in agreement is the sum of "Strongly agree" and "Agree" responses. The percentage in disagreement is the sum of "Strongly disagree" and "disagree" responses.

Table 4 Agreement analysis of factors

Factor ID	$\mathbf{a}_{WG}$ estimate	Level of consensus
f-13	0.81	Strong agreement
f-11	0.78	Strong agreement
f-08	0.77	Strong agreement
f-01	0.69	Moderate agreement
f-04	0.72	Strong agreement
f-21	0.73	Strong agreement
f-07	0.77	Strong agreement
f-20	0.78	Strong agreement
f-12	0.71	Strong agreement
f-03	0.79	Strong agreement
f-25	0.70	Strong agreement
f-15	0.76	Strong agreement
f-23	0.73	Strong agreement
f-24	0.75	Strong agreement
f-09	0.83	Strong agreement
f-17	0.80	Strong agreement

Table 5 Weightings and membership functions of critical factors (CFs) and critical factor groups (CFGs)

	Mean score		Weighting		Measurement of membership functions (MFs)		Criticality index		
CFG/CF	CF	CFG	CF	CFG	MFs of CFs	MFs of CFGs	Index	Weight	Rank
Compatibility		7.073		0.115		0.012 0.085 0.354 0.451 0.098	3.54	0.23	4
f-09	3.537		0.500		0.000 0.098 0.366 0.439 0.098				
f-17	3.537		0.500		0.024 0.073 0.341 0.463 0.098				
Competitive Advantage		10.976		0.179		0.016 0.082 0.316 0.399 0.187	3.66	0.24	3
f-15	3.659		0.333		0.000 0.122 0.293 0.390 0.195				
f-23	3.561		0.324		0.049 0.049 0.366 0.366 0.171				
f-03	3.756		0.342		0.000 0.073 0.293 0.439 0.195				
Trialability		8.585		0.140		0.000 0.024 0.071 0.488 0.416	4.30	0.28	1
f-13	4.415		0.514		0.000 0.024 0.000 0.512 0.463				
f-11	4.171		0.486		0.000 0.024 0.146 0.463 0.366				
Relative advantage		34.854		0.567		0.006 0.080 0.231 0.397 0.287	3.88	0.25	2
f-08	4.122		0.118		0.000 0.024 0.195 0.415 0.366				
f-01	4.000		0.115		0.024 0.049 0.171 0.415 0.341				
f-04	4.000		0.115		0.000 0.049 0.268 0.317 0.366				
f-21	3.951		0.113		0.024 0.049 0.146 0.512 0.268				
f-07	3.854		0.111		0.000 0.073 0.244 0.439 0.244				
f-20	3.829		0.110		0.000 0.073 0.244 0.463 0.220				
f-12	3.805		0.109		0.000 0.122 0.244 0.341 0.293				
f-24	3.561		0.102		0.000 0.146 0.341 0.317 0.195				
f-25	3.732		0.107		0.000 0.146 0.244 0.341 0.268				