CHAPTER (X)

BARRIERS TO BIG DATA TECHNIQUES APPLICATION IN CONSTRUCTION SAFETY, HEALTH AND WELLBEING

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ABSTRACT

The adoption of digital technologies such as big data analytics (BDA) for health, safety, and wellbeing (HSW) improvement in construction has increased but continues to experience challenges. Reviewing extant literature, this chapter identifies and discusses the barriers to HSW improvement using BDA. The barriers include technical issues such as the inability of existing machine learning techniques such as the fuzzy-neural method to predict HSW risks by analysing incident data, and the large size, heterogeneous and dynamic nature of construction accident data. While the socio-technical barriers include BDA skills shortage, the financial ones cover the high cost associated with BDA. Data dispute among companies, organisational culture, and ignorance of the potential of BDA in improving HSW which results in its limited acceptance and implementation in HSW are identified. There are also operational barriers in terms of digital poverty in construction, and supply chain issues where the fragmented supply chain of the industry and the uniqueness of projects do not facilitate a collaborative environment, a prerequisite for digital solutions. The implications of the findings include the need for an adequate legal framework international standard to settle the dispute between countries arising from data issues. Empirical studies to assess the barriers are recommended.

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Introduction and Rationale

The economic contribution of the construction industry to countries is evident in literature. For example, using selected studies from 1969 to 1998, Low and Lau (2019) demonstrate the correlation between construction activities and economic growth of countries in terms of per capita Gross Domestic Product (GDP). This is supported by recent data in the United States of America where the industry's contribution to GDP has increased from 3.4% in 2011 to 4.3% in 2020 (Statista, 2021). In 2018 in the United Kingdom (UK), the construction industry has contributed £117 billion to the nation's economy which is 6% of the total economy (Rhodes, 2019).

Conversely, the same industry contributes to economic losses through poor performance in terms of late project delivery, cost overrun (Mahamid et al., 2012) and poor health and safety records (Health and Safety Executive (HSE) 2020). For example, in Great Britain, £1.2 billion was lost to workplace injury and new cases of work-related ill health in the construction industry in 2018/19 (HSE 2020). About 2.1 million working days (full-day equivalent) were lost each year from 2017/18 to 2019/20 because of workplace injury and illness (HSE, 2020). Fines from prosecutions in 2019/20 in the industry amount to over £8.3 million (ibid).

Nevertheless, literature indicates that the adoption of digital technologies such as wearable technologies, robotics, and big data (BA) and analytics is one of the ways of improving health safety and well-being (HSW) in the construction industry (Awolusi et al., 2018; Yi & Wu, 2020; Haupt et al., 2019). For example, the monitoring and measurement of safety performance metrics in the industry can be done using wearable technologies (Awolusi et al., 2018). Big data frameworks are used for exploratory and predictive analytics of accidents data (Ajayi et al., 2019) which can help in accident prevention.

While extant literature covers digital construction technologies for improving HSW (Awolusi et al., 2018; Yi & Wu, 2020; Haupt et al., 2019), there are still knowledge gaps. For example, although the use of machine learning (a discipline in big data analytics (BDA)) is recommended for improving compliance with HSW legislation, little is understood about its application (Raliile and Haupt, 2020). Further, the barriers to the application of BDA in HSW such as the lack of its skills and knowledge requirements is poorly understood. Using a critical literature review, this chapter focuses on filling the knowledge gap. In particular, the study identifies and discusses the barriers to HSW improvement in construction using BDA. To the knowledge of the authors, this is the first study to address this knowledge gap.

Perspectives and Concepts

Big data and analytics

'*Big data are large and complex (unstructured, structured, and semi-structured)* data sets that *cannot be processed using the traditional processing techniques'* (Ajayi et al., 2019). Structured data can be data about construction sites in a table in a database where the site names, location codes, number of employees, and geographic locations are noted. The unstructured data include the output of Google Search, while the semi-structured ones are not limited to personal data which are stored in XML files. Big data is characterised by its volume (large quantity of data), velocity (the high speed at which the data is received and (perhaps) acted on), veracity (accuracy of data), and variety (range of data types of sources) (Zaslavsky, 2013). Indeed, its variety enables data handling using different syntactic formats (such spreadsheet, XML), data schemas and different meanings attached to the same syntactic forms (Curry, 2016). The large quantity of data that big data stores runs into terabytes (TB), petabytes (PB) and zettabytes (ZB). For example, using big data, Walmart imports over 2.5 petabytes of data when processing the transactions of over one million customers every hour (Griffith University, 2022). The velocity characteristic is epitomised in Coronel and Morris (2016) where the online shoppers' activities (for example, every click of the mouse) on the Amazon website are captured in real-time and used by Amazon. The sources of big data include sensors, log files, video or audio, devices, social media, websites, and transactional applications. Big data analytics is the entire process of analysing (finding patterns, trends, and relationships in) big data (with advanced techniques such as machine learning (including deep learning a type of it), data mining, predictive modelling, statistical and natural language processes) to develop intelligence and insight, enabling researchers, business users, and analysts to make fast and better decisions. The analyses are predictive, descriptive, and prescriptive.

Big data applications in construction health and safety

Digital technologies have the potential to revolutionise construction and HSW management. Using machine learning techniques such as fuzzy-neural methods or decision trees, incident data in construction are analysed and health and safety (H&S) risks are predicted to reduce accidents (Ajayi et al., 2019; Dehnath et al., 2016). For example, Zhu (2017) reports how the Suzhou fire brigade has used BP neural network and data machine learning algorithms on historical data on buildings and fires to establish fire risk prediction systems which increased the efficiency of fire prevention by 6 - 8 times. The motion tracking and analysis applied to a 3D skeleton motion model has predicted the behaviours of workers and injuries on construction sites which improve construction safety (Han et al., 2012). Big data and machine learning technologies are used for H&S risk-based inspections by labour inspectorates (European Agency for safety and health at work (EASHW), 2019). For example, the Norwegian Labour Inspection Authority has developed and successfully used the Risk Group Prediction Tool (RGPT) to identify the risk levels of companies or organisations (including construction) in Norway (EASHW, 2019). However, it cannot be used by another H&S inspectorate because of its data infrastructure and process (EASHW, 2019). The implication of risk-based inspection is that regulatory resources are focussed on where needed, especially where the regulator has limited resources. Nath et al. (2020) developed and tested deep learning approaches (a type of machine learning) for detecting personal protective equipment (PPE) (hat and vest) on construction sites in the US for contractor usage. In one of the approaches, using the single convolutional neural network, individual workers are detected, and the level of PPE compliance is verified. It produced 72.3% mean average precision. Deep learning can analyse videos, pictures and unstructured data in ways that machine learning cannot and it needs less ongoing human intervention. The successful use of the Bayesian network in forecasting occupational accident rates quantification, its consequences, and the equipment involved is reported in Papazoglou et al. (2015) and Meel (2007). This can be used in construction to forecast incidents, sources of accidents and to develop safe work arrangements.

The above shows how BDA is applied to HSW in construction to improve it. Evidence of the successful implementation of this is noted above. Further, the gains made by other industries in BDA has theoretical implications for construction. Ten studies that Hajakbaria and Minaei-Bidgoli (2014) review show where data mining techniques have been used to analyse accident databases proves that they reveal important patterns which traditional tools may not show. Using CRISP-DM data mining methodology and Clementine 12.0 software tool, one of the studies, Mirabadi and Sharifian (2010), applied association rules on 6500 records of accidents between 1996 and 2005 in Iran Railways. They found correlations and new patterns which were used to develop and improve preventive regulations and rules in the industry. The same argument can be made for construction.

Such potentials of BDA imply that it can answer penultimate business questions, ‘what is happening next?’ through predictive models and ‘how do we achieve the best outcomes?’ (optimisation, for example, injury prevention) (Schultz, 2013). If answered, they can improve HSW, productivity, employee and employer relationships, increase business profit, and create opportunities for data wastage reduction. In other words, they enable businesses and institutions including HSW regulators to make evidence-based and strategic decisions.

BDA can contribute to HSW improvement. However, its adoption for HSW risks analysis faces several challenges such as the lack of relevant knowledge (machine learning) for the analysis and it depends on high-performance computing (Ajayi et al., 2019). This hinders its adoption in the construction industry for HSW despite the huge amount of data that the industry produces. These barriers in the context of HSW risks need further exploration, hence the current study.

Barriers to Big data techniques applications in construction health and safety

Organisation and People

<u>BDA skills and knowledge requirements</u>

The literature review shows that BDA skills and knowledge requirements are a major challenge to HSW improvement using BDA. This stems from the lack of adequate policy and standards (Almeida and Calistru, 2013; Miller, 2014); the high level of skills required for BDA in H&S (Ajayi et al. 2019); the lack of clarity in the type of roles and responsibilities in BDA in construction (De Mauro et al. 2017; Puolitaival et al. 2018) which is also applicable to safety health and well-being; and the lack of skilled personnel (De Mauro et al., 2017). For example, H&S risk analytics responsibilities require machine learning knowledge and skills because of the large-scale data and high-performance computation (Ajayi et al., 2019). These skills are not commonplace in a typical construction company. Also, many construction companies do not have highly skilled H&S professionals but must outsource H&S activities which require a high level of skills, experience and knowledge.

<u>Organisational attitude and culture</u>

There is an agreement in the literature that organisational attitudes and culture towards digital technologies (such as BDA) has implications for their adoption and implementation (Almeida and Calistru, 2013; Bonesso et al., 2020; Chowdhury et al., 2019; Alalawneh and Alkhatb, 2020). The associated challenges include inadequate leadership (Chowdhury et al., 2019; Reinhard et al., 2016), poor attitude towards big data adoption (Chowdhury et al., 2019), lack of organisational support because of their values and norms (Alalawneh and Alkhatb, 2020; Chowdhury et al., 2019), and poor commitment from top management (Alalawneh and Alkhatb, 2020). Top management can foster big data adoption by providing incentive systems that are liked to BD and policies that reflect how the organisational values support BD adoption. Further, there is a lack of data-driven culture in some countries. For example, in a survey of 65 Fortune 1000 leading firms in the NewVantage Partners Executive Survey of 2019 shows that just 28.3% promote data culture and 31% were data-driven (NewVantage Partners 2019).

Optimum H&S management is underpinned by organisational commitment, support and strong leadership where it is a core value and norm in the organisation. In countries such as the UK, employers with five or more employees are legally required to have a written H&S policy where there is a statement of intent outlining the H&S aims signed by senior management, responsibilities for H&S, and arrangements. While this suggests some level of management commitment, at least in complying with the H&S legislation where applicable, it may be limited to minimum compliance with H&S legal requirements. Going above this (which in this instance includes adopting BDA for H&S risks) may be farfetched.

<u>Stakeholder interests</u>

Additionally, unlike other industries, the stakeholders in construction have different interests and values; hence, the adoption of BDA may be challenging because of a lack of agreement (Oudjehane and Moeini, 2017). When this is then applied to HSW, the interest may be reduced, especially when using BDA in H&S is not a legal requirement.

<u>Financial</u>

The cost implication of adopting BDA in the construction industry is adequately covered in the literature (Bilal et al., 2016; Oudjehane and Moeini, 2017; Madanayake and Egbu, 2017). HSW risks analytics is no exemption to this financial burden. In fact, 'infrastructure high cost' ranks highest among the 15 challenges of BDA implementation, as found by Madanayake and Egbu (2017). A lot concerning BD attract a cost, just like other digital technologies. For example, according to Bilal et al. (2016), organisations need to purchase licenses, establish data centres and invest in training or sourcing skilled persons for operating the system. This informs the perceived high cost associated with BDA which is exacerbated by H&S being wrongly viewed as an additional cost to businesses. This is particular with the small and medium businesses who consider the cost of investing in BDA and its return and see no value in it hence opt-out (Madanayake and Egbu (2017). This contributes to the digital transformation gap between large, and small and medium businesses (Dixon and Umeokafor, 2021). However, admitted that the inability to calculate the return on investment in BDA may explain the no perceived value in it (Wyman, 2018). More is required to change the 'H&S is a cost burden' paradigm in the construction industry, especially among small and medium businesses.

Data and process

<u>Nature of data and analytics</u>

Evidence in studies warrants the conclusion that various barriers to BDA for HSW risks centre on the nature of big data and analytics. The limitations due to the type of HSW data are covered in the literature (EASHW, 2019; Ajayi et al., 2019, 2020; Cha et al., 2017). In particular, H&S (or labour) inspectorate possess inspection object data on companies. However, the challenge here is that machine learning algorithms depend on unique identifiers to assign a predictive value to a company, but these inspection data may not be automatically identifiable with unique identifiers (EASHW, 2019). For example, in some construction sites without unique identifiers, machine learning algorithms cannot be used. Where available, the short duration of the existence of these sites means that machine learning algorithms are unable to predict the errors or success (EASHW, 2019). Another point against the machine learning algorithm is that it is unable to consider political views which are pertinent for risk-based targeted regulation which can help H&S regulators in managing resources in the regulatory system (EASHW, 2019). In particular, prioritisation is a core part of the risk-based targeting strategy for regulation adopted by HSW inspectors, but because of the constantly changing political context, the nature of risks that are worth prioritising is also highly dynamic. Further, different stakeholders in politics, employees, employers, media and industry, have different views of the type of risks that should be prioritised. Despite the dynamic ability of machine learning algorithms in learning success and failure, it usually misses these.
The implication of this is that despite the ability of BDA to transform H&S inspections, which is a core aspect of the H&S regulatory process, H&S inspectors who are unable to use them may become reluctant. However, the successful use of machine learning algorithms in predicting incidents based on safety inspection and observation data from hazard locations is reported in Schultz (2013). In particular, conclusions were drawn from trends and nuances in safety inspection and observation data to predict incidents that other indicators were unable to unearth.

Equally important is the size of the data (Almeida and Calistru, 2013; Ajayi et al.,2019, 2020; Cha et al., 2017). As information in big data is used for exploratory, descriptive, predictive and prescriptive analyses (Ajayi et al., 2019), the nature of H&S data just like many others make some analyses challenging. For example, H&S incident data set are unstructured, incomplete, unreliable and imbalanced to conduct effective predictive analysis resulting in predictive models (Cha et al., 2017; Ajayi et al., 2020). Consequently, data storage with conventional technologies for H&S risk advanced analytics in real-time is challenging (Ajayi et al. 2019; c.f. Almeida and Calistru, 2013). However, big data technologies can address this (Ajayi et al. 2019). Further, associated issues with machine learning algorithms in H&S risks big data analysis are noted in the preceding paragraph. Ajayi et al., (2019) conclude that 'health and safety risk analytics' is dependent on a high-performance computation and large-scale data storage requiring a large number of diverse data sets of health and safety risks, and machine-learning knowledge to successfully provide the needed analytical responsibilities.

Data privacy and security

Big data privacy and security challenges are documented in literature, for example, Almeida and Calistru (2013), Moura and Serrão (2015), Sun et al. (2021) and Yin et al. (2018). The risk to data security and privacy occurs during the information lifecycle where there are provenance, ownership, and classification of data issues (Almeida and Calistru, 2013; Moura and Serrão, 2015). There is a lack of security procedures, and data creation and collection process challenges (Moura and Serrão, 2015; Sun et al., 2021).

Sun et al. (2021) demonstrate how data limitations occur in terms of inadequate technological capacity for data security. Privacy protection methods result in little success in the big data environment because they are traditional anonymisation, fuzzy, and cryptography technology (Yin et al., 2018). While this may be suitable for conventional single-chain data lifecycle, the big data life cycle is an exception because of its complex multi-chain form which enables the 'sharing and trading links with more diverse data application scenarios and roles' in the big data environment (Sun et al., 2021).

Equally important is the incomplete data security legal system. Despite the existing laws and regulations in countries and economic communities on data security, the extant legislation is still complex, requiring further interpretations; the coordination between protection and development is inadequate (Sun et al., 2021). Some of these laws including legislations are difficult and expensive to interpret. The nature of big construction projects means that local or multinational companies (who in some cases are from different countries) carry them out where most of the laws and regulations on data security are local but big data usage can involve local and international organisations. This results in issues such as lack of clarity in data ownership once it is aggregated hence resulting in disputes among nations or companies (Sun et al., 2021; Kirkham et al., 2013). When these disputes occur, there is an inadequate legal framework of international standards to settle them (Sun et al., 2021). Other issues in big data governance include threats in cyberspace (Xu et al., 2021), a malicious act that can result in the damage or theft of data or its disruption.

Almeida and Calistru (2013) discuss the issues associated with accessing and sharing information the private organisations and institutions can be reluctant to do this among themselves or with their subcontractors. Possible explanations include the fear of reputational damage, the risks to competitive advantage, legal conditions and other external and internal factors (Almeida and Calistru, 2013; Bonesso et al., 2020). These challenges are also applicable to H&S big data and analytics or have implications for it. For example, the sensitive nature of H&S (including private information) makes its data more sensitive and delicate. When there are increased chances of lack of data privacy and security because of the above, ethical and security issues arise. By implication, organisations, especially those with poor worker HSW records, may be more reluctant to share data with others. Further, in the light of Almeida's and Calistru's (2013) above, a similar argument is made for the construction industry where according to Dixon and Umeokafor (2021) construction small and medium enterprises (SMEs) struggle with very low-profit margins and the adoption of digital technologies. The point is that SMEs encounter numerous significant challenges hence may view involvement in H&S big data and analytics as additional risk and expenses. Further, data security issues are likely to be worse in developing countries where there are weak, or no data protection laws.

Operational

Supply chain

Implementing digital technologies such as BDA in the construction industry encounters supply chain-related challenges. For example, because of its fragmented supply chain of the industry and the uniqueness of projects (which make replication difficult in that changes will need to be introduced to the project) a full-scale transformation (Madanayake et al., 2020). Digital solutions require a collaborative environment and long-term contracts. However, given the short-term contracts in construction, lack of trust and adversary nature therein, transparency in the supply chain is problematic (Madanayake and Egbu, 2017). By implication, implementing BDA in H&S in construction will be challenging.

Internet connectivity

Digital poverty in the construction industry and sites is also a challenge. For example, some construction sites may not have internet connectivity, but most, especially those in rural or undeveloped areas have low bandwidth which does not support real-time and instant data transmission to the BD repository (Bilal et al., 2016; Lippell, 2016). Stale offline data is not an alternative because it is useless for effective monitoring (Bilal et al., 2016). This argument can be repeated for the H&S dataset given its unstructured, incomplete, unreliable and imbalanced nature. However, the use of advanced sensor wireless networks can address this (ibid), but at a cost.

Implications for Practice and/or Research

To adequately improve the adoption of BDA for H&S, an adequate legal framework of international standards for settling the disputes between countries arising from data is pertinent. H&S BDA skills and knowledge requirements gap and shortage is evident in the study. Given the limited funds allocated to H&S in organisations and their attitudes towards it, more needs to be done to draw organisational attention to innovative H&S risks mitigation strategies. This calls for smarter ways of tackling BDA skills and knowledge requirements shortage for the greater good of digital transformation.

Just like other studies, the current study has limitations. For example, being a desktop study, the findings are subject to empirical investigation hence a survey on them is recommended and planned by the authors. Another study to identify the drivers to the adoption of BDA for HSW are recommended. However, being a stepping-stone to exploring the topic, this study can be used as a framework for subsequent studies on the topic.

Conclusions

This chapter identifies and discusses the barriers to HSW improvement in construction using BDA, an area underexamined. To the knowledge of the authors, this is the first study to address this knowledge gap. The barriers identified are categorised under organisation and people, data and process, and operational. The inability of existing machine learning techniques such as the fuzzy-neural method to predict HSW risks in construction by analysing incident data, and the large size, heterogeneous and dynamic nature of construction accident data is one of the major barriers. This is exacerbated by the lack of knowledge of the potentials of BDA in improving HSW which results in its limited acceptance and adoption in the construction industry. There is a digital transformation gap between SMEs and large enterprises which is also applicable to H&S big data analytics. However, the high cost associated with BDA, exacerbated by SMEs wrongly perceiving HSW as an additional cost and seeing no value in BDA investment (because of its limited scope in use — adoption in large projects), may explain this. But the lack of insight on the cost-benefit of investing in BDA for HSW may account for this. Other barriers include BDA skills and knowledge shortage, data-related disputes, and data security and privacy issues. In the light of the need to draw the attention of the organisations to innovative ways of addressing HSW risks, a legal requirement for this is recommended. An adequate legal framework of international standards to settle data-related disputes between countries is also recommended.

References

Ajayi, A., Oyedele, L., Akinade O., Bilal, M., Owolabi, H., Akanbi, L., Manuel, J., and Delgado, D., (2020) Optimised Big Data analytics for health and safety hazards prediction in power infrastructure operations. *Safety Science*, 125, May 2020, 104656

Ajayi, A., Oyedele, L., Delgado, J. M D., Akanbi, L., Bilal, M., Akinade, O., Olawale, O. (2019)

Big data platform for health and safety accident prediction, *World Journal of Science, Technology and Sustainable Development*,16 (1), 2-21,

Alalawneh, A. A. F., and Alkhatib, S. F. (2020) The barriers to big data adoption in developing economies. The *Electronic Journal of Information Systems in Developing Countries*, 1- 16.

Almeida, F. and Calistru, C. (2013) The main challenges and issues of big data management. *International Journal of Research Studies in Computing*, 2 (1), 11-20

Awolusi, I., Marks, E. Matthew Hallowell, M. (2018) Wearable technology for personalized construction safety monitoring and trending: Review of applicable devices. *Automation in Construction*, 85, 96-106

Bilal, M., Oyedele, L.O., Qadir, J., Munir,K.,Ajayi, S.O.,Akinade,O.,Owolabi, H.A., Alaka,H.A., and Pasha, M. (2016), "Big data in the construction industry: a review of present status, opportunities, and future trends", *Advanced Engineering Informatics*, 30 (3), 500- 521.

Bonesso S., Bruni E., and Gerli F. (2020) The Organizational Challenges of Big Data. In: Behavioural Competencies of Digital Professionals. Palgrave Pivot, Cham.

Chowdhury, T. & Adafin, J & Wilkinson, S. (2019). Review of digital technologies to improve productivity of New Zealand construction industry. *Journal of Information Technology in Construction*, 24, 569-587. 10.36680/j.itcon.2019.032

Coronel C and Morris S. (2016) Database systems: Design, implementation, and management. 12th ed. Boston (MA): Cengage Learning.

Côrte-Real, N., Ruivo, P., and Oliveira, T. (2020) Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? *Information & Management,* 57, 1-16

Curry, E (2016) The Big Data Value Chain: Definitions, Concepts, and Theoretical Approaches. In Cavanillas, J. M., Curry, E., and Wahlster, W. (edn.) New Horizons for a Data-Driven Economy: A Roadmap for Usage and Exploitation of Big Data in Europe. Switzerland: Springer Open, 29 - 37

Dakhil, A (2013) *The contribution of the construction industry to economic development in Libya.* Doctoral thesis, Liverpool John Moores University

De Mauro, A., Greco, M., Grimaldi, M., and Ritala, Paavo. (2017). Human resources for Big Data professions: A systematic classification of job roles and required skill sets. *Information Processing & Management*. 54 (5), 807-817 10.1016/j.ipm.2017.05.004.

Dixon, L. R., and Umeokafor, N.I, (2021) Determinants of Smart Technology adoption in the Construction Phase of Projects: A Scoping Study of the United Kingdom. In Windapo, A. O., Aiyetan, A. O., Umeokafor, N., Okoro, C., Adediran, A., Mtya. A., (Eds.). Ist Construction Business and Project Management (CBPM) Conference, Cape Town, South Africa 24 – 25 June 2021. ISBN – 978-0-620-91653-0.

European Agency for safety and health at work (2019) The future role of big data and machine learning in health and safety inspection efficiency. Retrieved on 29 Nov. 2021 from https://osha.europa.eu/en/publications/future-role-big-data-and-machine-learning-health-

Griffith University (2022) What Does Big Data Mean? Retrieved on Jan 31 2022 from https://www.futurelearn.com/info/courses/applied-big-data-analytics/0/steps/52404

Hajakbaria, M. S. and Minaei-Bidgoli, B (2014) A new scoring system for assessing the risk of occupational accidents: A case study using data mining techniques with Iran's Ministry of Labor data. *Journal of Loss Prevention in the Process Industries,* 32, 443-453

Han, S., Lee, S., & Peña-Mora, F. (2012). A machine-learning classification approach to automatic detection of workers' actions for behavior-based safety analysis. Computing in Civil Engineering (2012) (pp. 65-72).

Haupt, T.C., Akinlolu, M. and Raliile, M.T., 2019. Applications of digital technologies for health and safety management in construction. In: Sandanayake, Y.G., Gunatilake, S. and Waidyasekara, A. (eds). Proceedings of the 8th World Construction Symposium, Colombo, Sri Lanka, 8-10 November 2019, pp. 88 -97. DOI: doi.org/10.31705/WCS.2019.9.

Health and Safety Executive (HSE) (2020) Construction Statistics in Great Britain, 2020. Retrieved on 15 Nov. from https://www.hse.gov.uk/statistics/industry/construction.pdf

Kirkham, T., Winfield, S., Ravet, S., and Kellomaki S. (2013) The personal data store approach to personal data security. *IEEE Security & Privacy,* 11 (5), 12-19

Lippell, H. (2016) Big Data in the Media and Entertainment Sectors. In Cavanillas, J. M., Curry, E., and Wahlster, W. (edn.) New Horizons for a Data-Driven Economy: A Roadmap for Usage and Exploitation of Big Data in Europe. Switzerland: Springer Open, 245 - 259

Low, S. P. and Lau S. H. (2019) The Economy and the Construction Industry. *Construction Quality and the Economy,* 21–54. doi: 10.1007/978-981-13-5847-0_2

Madanayake, U. H. and Egbu, C (2017) A Systematic Review for the Challenges Related to the Implementation of Building Information Modelling, Big Data Analytics and Internet of Things (BBI) in the Construction Sector. *International Conference on Sustainable Futures- ICSF 2017.* Bahrain 26 - 27 Nov 2017 Applied Science University Bahrain.

Madanayake, U., H., Seidu, R. D and Bert Ediale Young, B., E. (2020) Investigating the Skills And knowledge Requirements for IOT implementation in Construction. Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management Detroit, Michigan, USA, August 10 - 14, 2020

Mahamid, I.; Bruland, A.; Dmaidi, N. (2012) Causes of Delay in Road Construction Projects. *Journal of Management in Engineering*, 28 (3), 300–310.

Meel, A., O'Neill, L.M., Levin, J.H., Seider, W.D., Oktem, U. and Keren N. (2007) Operational risk assessment of chemical industries by exploiting accident databases. Journal of Loss Prevention in the Process Industries, 20, 113-127

Miller, S. (2014). Collaborative approaches needed to close the big data skills gap. *Journal of Organization Design*, 3(1), 26—30.

Mirabadi and Sharifian, (2010) Application of association rules in Iranian railways (RAI) accident data analysis. *Safety Science*, 48,1427-1435

Moura J, and 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, 20-52. IGI Global.

Nath, N.D., Behzadan, A.H. and Paal, S. G. (2020) Deep learning for site safety: real-time detection of personal protective equipment. Automation in Construction., 112 (2020).

NewVantage Partners (2019) Data and Innovation: How Big Data and AI are Accelerating Business transformation. Retrieved on 11 March 2022 from https://www.tcs.com/content/dam/tcs-bts/pdf/insights/Big-Data-Executive-Survey-2019-Findings-Updated-010219-1.pdf

Oudjehane, A and Moeini, S (2017) Big data in construction projects: Risk and opportunity management. Turning Knowledge into Practice, May 4-5, 2017. Retrieved on 20 Oct. 2021 from http://pmsymposium.umd.edu/pm2017/session/big-data-in-construction-projects-risk-and-opportunity-management/

Papazoglou, I., Aneziris, O., Bellamy, L., Ale, B. and Oh, J. (2017). Quantitative occupational risk model: single hazard, *Reliability Engineering & System Safety*, 160, 162-173.

Puolitaival, T., Kestle, L. and Kalle Kähkönen (2018) What's the real story around digital technologies in construction management? 42nd AUBEA Conference 2018: Educating Building Professionals for the Future in the Globalised World, 251 -260

Raliile, M. T. and Haupt, T. C. (2020) Machine learning applications for monitoring construction health and safety legislation and compliance. In Askarinejad, H., Yazdani, S., and Singh, Proc. of International Structural Engineering and Construction. Emerging Technologies and Sustainability Principles. www.doi.org/10.14455/ISEC.2020.7(2).CON-23.

Reinhard, G., Jesper, V. and Stefan, S. (2016) Industry 4.0: Building the digital enterprise, 2016 Global Industry 4.0 Survey. DOI:10.1080/01969722.2015.1007734

Rhodes, C. (2019) Construction industry: statistics and policy. House of Commons Library. Briefing paper: Number 01432. Retrieved on 17 Nov. 2021 from https://researchbriefings.files.parliament.uk/documents/SN01432/SN01432.pdf

Schultz, G. (2013) The Era of Big Data Analytics in Safety. Safety Matters, Nov. 2013. Retrieved on 14 June 2021 from http://www.naylornetwork.com/ngc-safetyMatters/articles/index.asp?aid=241739&issueID=38258

Statista (2021) Value added by the construction industry as a share of gross domestic product in the United States from 2007 to 2020. Retrieved on 17 Nov. from https://www.statista.com/statistics/192049/value-added-by-us-construction-as-a-

Sun, L., Zhang, H., Fang, C., (2021) Data security governance in the era of big data: status, challenges, and prospects. *Data Science and Management*, 2, 41-44.

Wyman, O. (2018) Digitalisation of the construction industry: The revolution is underway. Retrieved on 29 Sept. 2020 from https://www.oliverwyman.com/our-

Xu S., Yung M., and Wang J. (2021) Seeking foundations for the science of cyber security. *Information Systems Frontier*, 23, 263-267

Yi, X. Z., & Wu, J. Y. (2020). Research on Safety Management of Construction Engineering Personnel under "Big Data + Artificial Intelligence". *Open Journal of Business and Management,* 8, 1059-1075

Yin, C., Xi, J., Sun, R., and Wang J. (2018) Location privacy protection based on differential privacy strategy for big data in industrial Internet of Things. IEEE Transactions on Industrial Informatics, 14 (8), 3628-3636

Zaslavsky, A., Perera, C., and Georgakopoulos, D. (2013) Sensing as a Service and Big Data. Proceedings of the International Conference on Advances in Cloud Computing (ACC), Bangalore, India, July, 2012

Zhu, Y. M. (2017). Data-Driven Fire Risk Prediction System. *Fire Science and Technology*, 36, 1011-1013.

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