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A case study on the implementation of location tracking technologies for productivity monitoring: understanding workers' acceptance and socio-technical implications

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Automated real-time data collection is becoming more prevalent in construction, with workers' location data being a pivotal component in detecting poor logistics and inefficient construction flows. However, the collection of location data for productivity monitoring raises significant concerns about privacy and wellbeing implications for workers. Implementing such technological solutions requires an understanding of how humans may respond to sensor-based automated data collection, making this a socio-technical issue. This study identifies the drivers of construction workers' acceptance of radio-based location tracking technology for productivity measurement using a modified Technology Acceptance Model (TAM) and offers a sociotechnical understanding of technology acceptance with implications for managing how new technologies are introduced on construction projects. Using a large residential project in Lima, Peru as a case study, construction workers were monitored using Bluetooth Low Energy (BLE) technology, and data were gathered using mixed methods. A k-means clustering analysis showed two forms of acceptance among workers: *supporters* (37%) and *acceptance with reservations* (63%). Partial least squares Structural Equation Modelling (PLS-SEM) results showed that perceived usefulness and perceived stress underpinned workers' attitudes and intention to accept the technology. Perceived privacy risk, however, emerged as the sole most significant predictor at the end of the monitoring process. Findings further suggest that workers' acceptance of the technology is influenced by the perception that it is also beneficial for safety management. Building on the preceding, the paper highlights the need for employee orientation focused on addressing perceived privacy concerns by leveraging positive perceptions about using monitoring technologies for improving onsite safety, logistics and productivity. This requires management of construction firms to develop narratives that reflect their goals for rolling out technologies in ways that ensure workers' buy-in, and a re-focus on problem framing and collective approaches to identifying functional and less intrusive forms of monitoring technologies.

KEYWORDS

real-time location monitoring, technology acceptance, construction worker, productivity monitoring, socio-technical implications, case study

1 Introduction

There is extensive documentation indicating that the economic productivity of construction at the sector level, as measured by gross value-added per hour worked, has not shown any significant improvement over recent decades (Barbosa et al., 2017; ONS, 2021). The increased adoption of lean construction techniques, off-site manufacturing, and digital technologies has opened the doors for improved project-level production control and performance (Farmer, 2016; PwC, 2018; Lagos and Alarcón, 2021) which ultimately should reflect in sectoral productivity improvement. Yet, construction organisations encounter a challenge with capturing, integrating, processing, analysing, and interpreting construction data for production control and productivity improvement (Hasan and Sacks, 2023).

A newly proposed solution to address the productivity challenges in construction management is Digital Twin Construction (DTC), which aims to leverage real-time data from site monitoring technologies for accurate as-built information and efficient planning, production, safety, and productivity optimisation (Sacks et al., 2020). The successful implementation of DTC requires simultaneous analysis of planned and actual data including programme and production plans as well as production rates and labour utilisation (Murguia et al., 2022). However, one challenge lies in measuring labour utilisation in critical activities while accounting for unproductive time caused by suboptimal construction flows due to poor planning and logistics. Labour and production data can be obtained through automated means such as radio-based or vision-based tracking technologies (Zhang et al., 2018; Cai and Cai, 2020). Radio-based systems require the attachment of devices to workers for real-time dashboard monitoring of their locations, with analytics providing insights into time spent in production areas (Zhao et al., 2019). Vision-based methods employ outdoor cameras mounted on cranes or nearby buildings for overall monitoring, whilst indoor scanning is utilised for more granular as-built information. However, ethical concerns regarding digitalisation's impact on workers must be considered. Specifically, there are questions about construction management teams' responsibility when it comes to accessing workers' location data for productivity monitoring–even if anonymized–and whether workers agree to be monitored.

Previous studies have investigated the use of motion and physiological sensors to detect safety hazards and to continuously monitor construction worker's health (Ahn et al., 2019). Moreover, Rao et al. (2022) found that contemporary studies of real-time monitoring of construction sites entails observing employees' hazardous conduct, physiological state, health status tracking as well as identifying unsafe situations (Awolusi et al., 2018; Hwang et al., 2018; Ahn et al., 2019). Furthermore, research has explored critical success factors for assessing the impact of wearable sensing devices for health and safety monitoring on construction workers (Nnaji and Awolusi, 2021; Okpala et al., 2021). Nevertheless, no prior studies appear to examine how location-tracking technology for *productivity monitoring* impacts workers' behaviour. According to Paneru and Jeelani (2021), there is a possibility that construction workers may experience increased levels of anxiety and stress due to the perception of constant monitoring, ultimately leading to negative impacts on their mental health. Additionally, some countries like New Zealand have expressed concerns about data protection and privacy management for frontline workers subjected to productivity monitoring systems (Wu et al., 2022).

The factors influencing the acceptance of location tracking technologies for productivity monitoring might not align with the determinants associated with the acceptance of wearable sensing devices for occupational health and safety, the foci of previous studies. The fear of job loss, constant surveillance, and the perception that taking long breaks or straying from their designated work area might be seen as unproductive could impact workers' acceptance of location tracking technologies for productivity monitoring. These issues are yet to be explored empirically. Therefore, additional work evaluating workers' acceptance towards this technology is crucial to expand existing understanding of location tracking technologies for productivity improvement in construction.

Moreover, this study also takes inspiration from the broader sociotechnical tradition for technology studies (Harty, 2005; Schweber and Harty, 2010; Sony and Naik, 2020) and conceptualises technology acceptance as a function of sociotechnical interactions between human actors and technical components of technology. Different actors construct the meaning of technology differently, which suggests that a sociotechnical approach is needed to understand better how workers perceive automated location-tracking technologies. Existing research has investigated workers' acceptance of wearable sensing devices for occupation safety and health from a critical success factors perspective, with limited consideration to social aspects to technology (Choi et al., 2017; Huang et al., 2021; Man et al., 2021; Okpala et al., 2022). Therefore, technology acceptance is complemented with a sociotechnical view to establish the non-technical considerations that are significant for achieving desired levels of technology acceptance. Thus, this study offers both quantitative and qualitative insights for a comprehensive understanding of how new technologies can be successfully rolled out at construction sites. Thus, the objectives of this study are: 1) To identify the levels of acceptance of location-monitoring technologies for productivity monitoring, 2) To determine the factors that influence construction workers' willingness to accept location-tracking technology for productivity monitoring, and 3) To

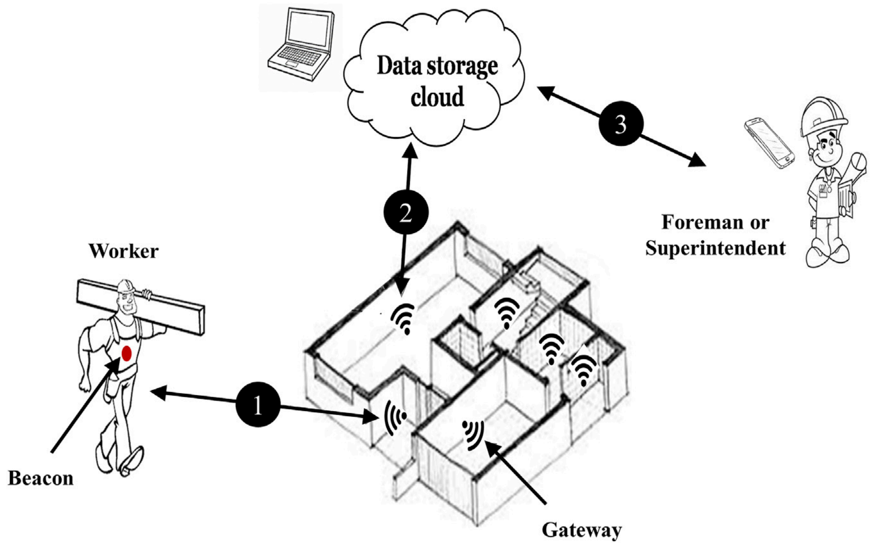

FIGURE 1
Methodology for monitoring construction workers using BLE technology.

describe the socio-technical implications of monitoring technologies within organisational and project contexts.

In this study, Bluetooth low energy (BLE) technology was selected as the radio-based technology for indoor tracking of construction workers (Zhao et al., 2019). The methodology for monitoring construction workers using BLE technology is presented in Olivieri et al. (2017) and Zhao et al. (2021) and adapted in Figure 1. Workers wear beacons attached to either their helmets or armbands, transmitting data via Bluetooth Low Energy (BLE) technology at a frequency of 1 Hz, corresponding to one-second intervals. These signals are communicated to gateways strategically positioned on each floor (link 1). These gateways continually capture the periodic signals emitted by nearby beacons and relay this data to the cloud-based system utilizing the Message Queuing Telemetry Transport (MQTT) protocol (link 2). The cloud-based system processes and manages this information in real-time, offering precise details about the workers' locations. Site management teams can access this information through a web-based application (link 3). For further information about the cloud infrastructure, refer to Zhao et al. (2019).

The implementation of this system offers a suitable setting for understanding the influence of productivity monitoring technologies on construction workers. Prior studies have not examined worker acceptance towards BLE technology for productivity monitoring, making this research significant. Unlike previous studies which collected worker's reaction to technology data based on induction (Choi et al., 2017) or surveyed workers with general construction experience rather than specific technology exposure (Huang et al., 2021), this study occurs in a construction site environment where a location tracking system was implemented. Thus, data for this study was collected "*in situ*", and directly based on workers' first-hand experience of the technology.

This paper is structured as follows. Section 2 presents the theoretical framework and hypotheses whilst Section 3 presents a socio-technical view of technology acceptance. Section 4 describes the case study research approach and the context under study. Section 5 presents the outcomes of quantitative data analysis whilst Section 6 presents the qualitative data analysis results. Section 7 presents the discussion of the findings including the theoretical and managerial implications. Finally, Section 8 presents the conclusions and future lines of inquiry.

2 Location-tracking technology acceptance

Vision-based monitoring technologies in the construction industry support the identification of workers' movement patterns and activity recognition (Luo et al., 2018). However, workers are increasingly becoming more aware of their privacy rights at work since prior studies have suggested that explicit consent from workers were often needed for real-time monitoring in construction (Kim et al., 2019). On the other hand, radio-based monitoring technologies with passive and non-image-revealing features such as Radio frequency identification (RFID) or Bluetooth Low Energy (BLE) have been proposed (Teizer et al., 2020; Zhao et al., 2021). Nonetheless, the fact that workers are already aware of the ongoing monitoring process may impact workers' wellbeing and stress (Nazareno and Schiff, 2021), highlighting the need for a better understanding of how monitoring technology influences workers' behaviour. Therefore, it is of high importance to understand the influence of monitoring technologies on workers. Then, a clearer relationship between the adoption of a monitoring system in construction and workers' reactions can be drawn to improve production control and construction management. As such, this study applies a modified Technology Acceptance Model (TAM) for analysing the factors of workers' acceptance of monitoring technologies.

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2.1 Technology acceptance model (TAM)

TAM is a seminal model developed by Davis et al. (1989) and Davis (1993) that explains the drivers for users' acceptance of new technologies. The model assumes that users are likely to adopt a technology if they perceive that the technology is useful for their individual performance (i.e., perceived usefulness) and that it is easy to learn (perceived ease of use). The model predicts that "Perceived Usefulness" and "Perceived Ease of Use" influence "Attitude Towards Using". Moreover, "Attitude Towards Using" influences "Behavioural Intention to Use" which in turn influences "Actual System Use". TAM or modified versions of TAM were used in construction technology research such as user's acceptance of virtual reality training and education (Zhang et al., 2022), construction professionals' acceptance of web-based training (Park et al., 2012) and mobile computing devices (Son et al., 2012), construction worker's acceptance of wearable technologies (Choi et al., 2017), BIM in design organisations (Son et al., 2015) and BIM adoption among contractors (Murguia et al., 2023).

In this research, the construct "Perceived Usefulness" was selected to capture frontline workers' belief of how the monitoring system helps to improve their productivity as well as logistics of material and equipment and the quality of the work area. Similarly, "Attitude Towards Using" was also selected as a strong predictor as suggested by previous studies. However, the factor "Perceived Ease of Use" was not deemed suitable for predicting workers' acceptance for several reasons. Firstly, workers do not actively use the technology, but rather simply carry the beacons. Secondly, workers do not need any training to use the technology, including the beacons and gateways. And thirdly, the technology is primarily used by the site management team and not by the construction workers, who do not need to learn how to use the technology.

2.2 Perceived privacy risk

Privacy risk is defined as the expected loss potential due to releasing personal information to the firm (Li et al., 2014). Workers' decision to accept monitoring systems involves a trade-off between potential benefits and perceived privacy risks as real-time location information is released to the employer (Gao et al., 2015). The potential threat to the individual's privacy can make users reluctant to use wearable devices as data is transmitted wirelessly between the sensor device and the cloud (Choi et al., 2017). Moreover, some workers might believe that the real-time location data can be used to monitor their individual performance and, thus, the employer can terminate their contracts if not performing well. Workers with high privacy risks can perceive a greater threat to their job security, therefore they would be unwilling to be monitored or accept new technology. More specifically, frontline workers could be uncomfortable when their location information at the workplace is shared with site engineers during working time and/or meal and toilet breaks (Choi et al., 2017).

Previous studies in the realm of health and safety have incorporated "Perceived Privacy Risk" to study the acceptance of wearable devices to capture physiological data. Awolusi et al. (2018) argued that wearable systems are commonly criticised for privacy, security, and legal issues. Similarly, Choi et al. (2017) claimed that people tend to be sensitive towards sharing relevant information about them, especially if the information will bring potential harm. Ahn et al. (2019) also found that perceived privacy risk was a predictor of intention to use technologies for automated safety measurement. Hence, "Perceived Privacy Risk" is an essential factor worth investigating for workers' acceptance of automated productivity monitoring systems.

2.3 Perceived stress

Automation might improve productivity although it may also have mixed or negative impacts on worker wellbeing (Nazareno and Schiff, 2021). Moreover, construction professionals and construction workers experience high levels of stress in the workplace which can harm their psychological wellbeing (Love et al., 2010; Bowen et al., 2014). The wellbeing of construction workers is of paramount importance to ensuring healthy, safe, and productive construction sites. The study of psychological stress in the construction industry is growing in the literature (Love et al., 2010; Jebelli et al., 2019; Dennerlein et al., 2021; Palaniappan et al., 2022). However, the introduction of recent technology such as an automated real-time location tracking system for productivity monitoring can be a technological stressor in the workplace for monitored workers.

Previous research has acknowledged that job insecurity is a dimension of occupational stress (Alsulami et al., 2021). Hellhammer et al. (2010) argued that the perception of social hierarchy (managers always knowing the position of workers) and the concern with possible future events (fear to lose their job) are common sources of stress. Jandl et al. (2021) stressed that location data can be used to track productive working hours, and this can lead to additional burden or stress for employees. Thus, perceived stress due to the introduction of a monitoring system should be proactively managed to mitigate its ill side effects which range from making errors to causing accidents (Umer, 2022) and to overcome resistance to adoption. The existing body of research has measured stress-related psychological symptoms such as tension, lack of confidence, sadness, depression, or dissatisfaction (Abbe et al., 2011; Bowen et al., 2014). Hence, measuring perceived stress would be fundamental to understanding frontline workers' acceptance of automated location tracking systems for productivity monitoring.

2.4 Social factors

Drawing from the Theory of Reasoned Action (TRA), "Subjective Norm" was defined as the individual's perception that people who are important to them think they should perform a specific behaviour (Fishbein and Ajzen, 1975). "Subjective Norm" was applied by Davis et al. (1989) for the case of individual acceptance of technologies and found that "Subjective Norm" explains the individual's intention to adopt a new system. On the other hand, the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) presented the construct "Social

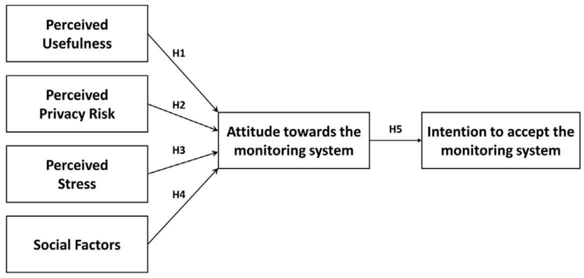

FIGURE 2
Theoretical framework.

Influence" as a predictor of intention to adopt new technologies. "Social Influence" was defined as the degree to which an individual perceives that important others believe they should use new technology. Thompson et al. (1991) developed a model for personal computer (PC) utilisation and applied "Social Factors" as a determinant for the use of PCs. "Social Factor" was defined as the individual's internalisation of the group's subjective culture and the specific relationships that the individual has made with others in specific social situations. Together, these studies suggest that social interactions are key determinants of the acceptance and use of technologies.

The definition provided by Thompson et al. (1991) is closer to the case of automated monitoring systems as the implementation of location-tracking technologies might change the relationships between actors in a specific social situation determined by the introduction of new technology. For instance, the deployment of an automated location monitoring system might inhibit workers' free movement as long breaks or being outside their working area can be perceived as unproductive. Also, workers might perceive that the knowledge of their location is not acceptable to their supervisors or peers, thus, affecting their relationships. Hence, this research defines "Social Factors" as the extent to which construction workers believe that automated location tracking systems affect their relationships with other people on the job site and their free movement.

2.5 Theoretical framework

Based on the TAM model and the associated factors found in the literature, Figure 2 presents the theoretical framework and hypothesis for this study. Specifically, the key hypotheses are:

H1: "Perceived Usefulness" (PU) is positively associated with workers' attitude towards the monitoring system (ATT)

H2: "Perceived Privacy Risk" (PPR) is negatively associated with workers' attitude towards the monitoring system (ATT)

H3: "Perceived Stress" (PS) is negatively associated with workers' attitude towards the monitoring system (ATT)

H4: "Social Factors" (SF) is negatively associated with workers' attitude towards the monitoring system (ATT)

H5: "Attitude towards the monitoring system" (ATT) is positively associated with the intention to accept the monitoring system (INT)

3 Beyond TAM: a socio-technical view of technology acceptance

The sociotechnical studies (STS) view of technology is situated in the broader viewpoint of the sociology of technology (Geels and Kemp, 2007). Fundamentally, the STS view offers an approach that contrasts long-held views suggesting that technology and its adoption is a rigid process that is primarily techno-centric (Harty, 2005). Adopting any sociotechnical network approach that follows the broader STS tradition requires a departure from a rigid conceptualisation of technology adoption that favours compartmentalisation of its adoption with a focus mainly on the technical aspect (i.e., the design and composition) (Bergek et al., 2015). For a better understanding of the unique, context-specific nature of technology and its adoption, the STS approach comprises an array of network approaches (e.g., the Social Construction of Technology, Actor-Network Theory and the Large Technological Systems) which provide a *"schema which acknowledges all those institutions, artefacts and arrangements within which the adoption, configuration and use of those technologies take place–including the knowledge and expertise which have created technologies and are embedded in them…"* (Williams and Edge, 1996) (p. 875).

The STS view of technology offers a lens through which interactions between humans and technology can be examined in an environment (Schweber and Harty, 2010). From this perspective, the development and use of any kind of technology is not considered devoid of social influence; its identity is embedded in the characteristics of the context in which it is found (Harty, 2005; Schweber and Harty, 2010). Here, context refers to the human actors, the institutions and setting within which the development, adoption, and use of the technology occur (Williams and Edge, 1996; Sony and Naik, 2020). Such a viewpoint is crucial in extending existing knowledge about technology acceptance in construction project settings from the establishment of quantitative relationships to understanding how social (human, organisational and contextual) elements play crucial roles as strong factors in shaping acceptance outcomes (cf. Oesterreich and Teuteberg, 2019; Shojaei and Burgess, 2022).

Construction project delivery involves a wide array of human actors and technical artefacts within a technological mix engaged towards the completion of a built asset (Harty, 2005). Relatedly, construction firms employ a blend of tacit and explicit technology such as construction plant and equipment, project techniques and management processes, as well as intuitive ideas that are incorporated in project design, and managing construction processes (cf. (Harty, 2005; Shojaei and Burgess, 2022)). The introduction of any new technology is therefore intrinsically situated within this mix of interacting factors. The interactions influence how new technology will be perceived, accepted, and consequently adopted. As part of these interactions, we argue that perceptions about a technology reflect the collective views (technological frame) actors hold, which in turn shape their responses concerning the adoption and use of new technical components. Understanding how workers would embrace new

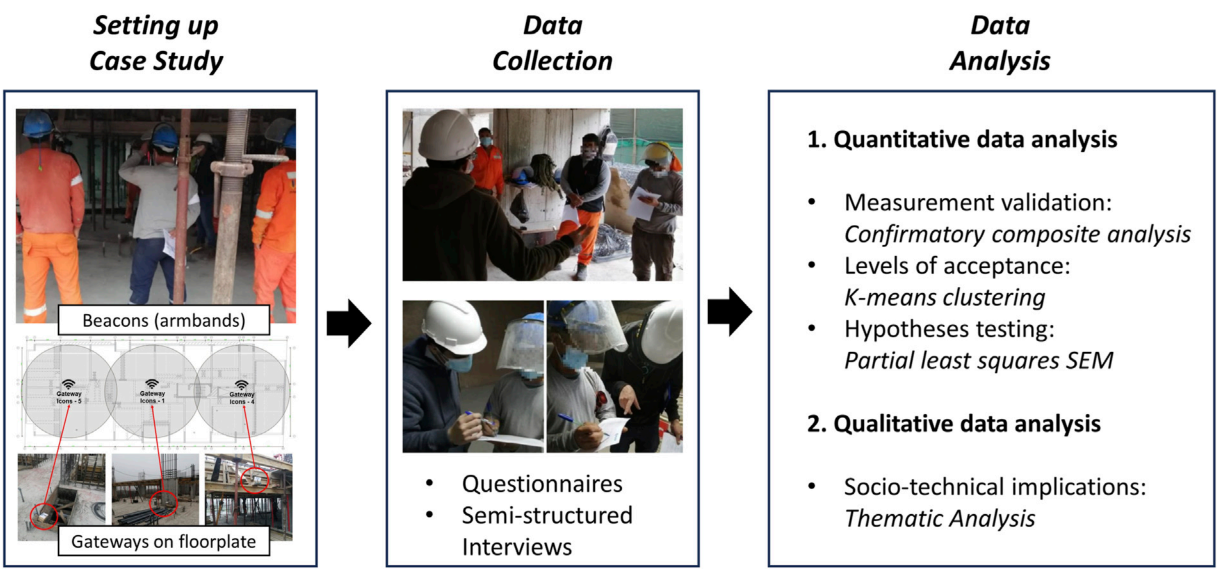

FIGURE 3
Research method.

technology is therefore incomplete if examined only from the angle of identifying perceptions without an understanding of the wider human, organisational, and contextual factors influencing acceptance, adoption, and eventual use. We take forward the foregoing view in examining workers' perceptions about the acceptance and use of tracking technologies on a construction site.

4 Research method

4.1 Case study research

To empirically analyse the theoretical framework and examine the sociotechnical environment, the authors selected a deductive case study approach because it allows for explaining causal links or associations in real-world interventions within the context in which they occurred (Yin, 2014). Since the adoption of location-tracking technologies is not yet a common industry practice, it is rare to find projects using such systems. Therefore, a purposeful intervention in a single-case study, Project Alpha, was selected. Within the case study, construction workers served as an embedded unit of analysis. First, the project depicts the *common* case defined by Yin (2014). For instance, Project Alpha is managed by a general contractor who employs multiple trade contractors to carry out construction activities such as rebar, formwork, and concrete. Second, an in-depth examination of workers' perception and acceptance of real-time location technologies for productivity monitoring requires maximising the number of observations within the case to analyse a phenomenon previously inaccessible (Yin, 2014). Third, a single-case study allows for collecting data at two or more different points in time. In the case of monitoring construction workers, a two-week interval is suitable for revealing changes between workers' initial perceptions of the technology and their perceptions after being monitored. An effective evaluation of a case study should employ a variety of sources of evidence to verify and support the results, including both quantitative and qualitative data (Yin, 2014). This research selected questionnaire data to identify the levels of acceptance and validate the theoretical framework, and semi-structured interviews to delve into the socio-technical aspects related to technology acceptance. Under this approach, the researchers first conducted quantitative research and then built on the results to explain them in more detail with qualitative data (Creswell, 2014). A summary of the research method is shown in Figure 3.

4.2 Research design

The next step in the methodology was to design a questionnaire to obtain empirical data. The measurement items were adapted from different sources and some others were purposively designed for this study. "Perceived Usefulness", "Attitude towards the monitoring system", and "Intention to accept monitoring system" were adapted from Davis et al. (1989), Davis, (1993) and Venkatesh et al. (2003). "Perceived Privacy Risk" was adapted from Awolusi et al. (2018) and Choi et al. (2017) who studied the effect of wearable devices for health and safety monitoring. Hellhammer et al. (2010) argued that self-report questionnaires are the most common method of measuring "Perceived Stress". Thus, the questionnaire items for "Perceived Stress" were adapted from Abbe et al. (2011) and Bowen et al. (2014). The "Social Factors" items were extracted from Urbina (2019).

A summary of the variables used in this stage is shown in Table 1. Likert-type scales with a mid-point (e.g., 5-point scale) have been criticised as respondents might interpret the mid-points in ways not int ended by the researchers, therefore, introducing bias in the data. Moreover, participants without knowledge of the topic or undecided participants could still respond to the questions by selecting the mid-point (Baka et al., 2012). Given the nature of this study, responses were recorded on a 4-point scale (1 = Strongly

TABLE 1 Assessment items.

Latent factor	Variable	Assessment item	Adapted from
Perceived Usefulness (PU)	PU1	The monitoring system improves my productivity	Davis et al., 1989; Davis (1993), Son et al., 2012; Urbina (2019), Wong et al. (2021)
	PU2	The monitoring system improves the distribution of materials and equipment	Davis et al., 1989; Davis (1993), Urbina (2019)
	PU3	The monitoring system improves the quality of my work area	Davis et al., 1989; Davis (1993), Urbina, 2019; Wong et al. (2021)
	PU4	The monitoring system improves the instruction of my supervisors	Davis et al., 1989; Davis (1993), Urbina (2019)
Perceived Privacy Risk (PPR)	PPR1*	I am comfortable with letting the company know the time I spent with my co-workers	Choi et al. (2017), Awolusi et al. (2018)
	PPR2*	I am comfortable with letting the company know the time I spent outside my work area	Choi et al. (2017), Awolusi et al. (2018)
	PPR3*	I am comfortable with letting the company always know my position	Choi et al. (2017), Awolusi et al. (2018)
	PPR4*	I am comfortable with letting the company always record my position	Choi et al. (2017), Awolusi et al. (2018)
Perceived Stress (PS)	PS1	The monitoring system makes me feel upset	Abbe et al. (2011), Bowen et al. (2014)
	PS3	The monitoring system makes me feel worried to lose my job	Abbe et al. (2011), Bowen et al. (2014)
	PS4	The monitoring system makes me feel nervous and stressed	Abbe et al. (2011), Bowen et al. (2014)
	PS5	The monitoring system makes me feel tired	Abbe et al. (2011), Bowen et al. (2014)
Social Factors (SF)	SF1	The monitoring system affects the interaction with my supervisor	Urbina (2019)
	SF2	The monitoring system affects the interaction with my peers	Urbina (2019)
	SF3	The monitoring system affects my free movement	Davis et al., 1989; Davis (1993), Urbina (2019)
Attitude towards the monitoring system (ATT)	ATT1	The monitoring system is a good idea	Davis et al. (1989), Venkatesh et al. (2003), Wong et al. (2021)
	ATT2	I like being monitored	Davis et al. (1989), Venkatesh et al. (2003), Wong et al. (2021)
	ATT3	The monitoring system makes my work more interesting	Davis et al. (1989), Venkatesh et al. (2003), Wong et al. (2021)
Intention to accept the monitoring system (INT)	INT1	I would like the company to implement monitoring systems on the next project	Davis et al. (1989), Venkatesh et al. (2003), Wong et al. (2021)
	INT2	I would like the company to implement monitoring systems as soon as possible	Davis et al. (1989), Venkatesh et al. (2003), Wong et al. (2021)
	INT3	I would like to help the company to implement monitoring systems	Davis et al. (1989), Venkatesh et al. (2003), Wong et al. (2021)

Note: * Reversed scored.

Disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree) with a "No Opinion" option. This allowed participants to select "No Opinion" when confronted with questions they are not comfortable with, therefore, reducing bias in the data. The questionnaire was piloted with a crew of fifteen construction workers to ensure the face validity of the constructs. Finally, a semi-structured interview was designed to gather qualitative data to draw insights into the socio-technical aspects of technology acceptance. Construction workers were asked questions regarding the perceived usefulness of the monitoring system, the perceived privacy risk, their individual reactions to the technology and the degree of acceptance of further monitoring, as shown in Table 2.

4.3 Data analysis methods

Confirmatory composite analysis (CCA), k-means clustering, and partial least squares structural equation modelling (PLS-SEM) were selected as the quantitative data analysis methods. CCA was used to assess the construct validity of the multi-item factors. Construct validity is the extent to which a set of observed variables reflects the theoretical factor they are expected to measure (Hair et al., 2021). Construct validity is made up of *convergent* and *discriminant* validity. *Convergent* validity is the extent to which a measure correlates positively with alternative measures of the same construct. To evaluate convergent validity,

TABLE 2 Interview questions.

Number	Question
Q1	Did you feel that the real-time monitoring system put at risk your privacy? Why?
Q2	What did you feel about the fact that the management team always knew your position?
Q3	Did you feel that the monitoring system affected your job stability? Why?
Q4	Would you say that the monitoring system improves productivity and daily progress?
Q5	Would you accept being monitored again? Why?
Q6	Would you support the monitoring system becoming a widespread industry practice?

researchers should consider the outer loadings of the indicators, construct reliability (CR), and the average variance explained (AVE). A common rule of thumb is that the standardised outer loadings should be 0.7 or higher, CR above 0.7, and AVE of 0.5 or higher. *Discriminant* validity is the extent to which a latent factor is distinct from other latent factors. Fornell and Larcker (1981) recommended comparing the square root of the AVEs for any two constructs with estimated correlations between these two constructs. The square root of AVE should be greater than the correlation estimate. Passing this test provides evidence of discriminant validity.

Second, K-means clustering is a method used for grouping similar data points based on their characteristics. The k-means algorithm works by partitioning a dataset into "k" clusters, where each cluster represents a group of data points that are similar to each other (Wu et al., 2008). The algorithm starts by randomly selecting "k" data points as the initial centroids, and then iteratively assigns each data point to the nearest centroid, re-calculates the centroids based on the mean of the data points in each cluster, and repeats the process until convergence (Celebi et al., 2013). K-means clustering can be an effective tool for identifying groups or levels of acceptance of new technology because it allows for the classification of individuals based on questionnaire responses. By clustering individuals with similar characteristics and behaviours, researchers can gain insight into the different levels of acceptance. This information can then be used to tailor strategies to specific groups or to better understand the reasons why certain groups are more or less likely to accept the technology.

Third, Structural equation modelling (SEM) is a second-generation multivariate analysis technique that overcomes the weaknesses of first-generation techniques such as analysis of variance or multiple regression. SEM has the potential to analyse path diagrams when these involve latent factors with multiple variables (Gefen et al., 2011). As such, SEM integrates the measurement model (latent factors and observed variables) and the hypothesised paths (structural model). There are two types of SEM: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) (Hair et al., 2011). The latter is primarily used for theory testing and determines how well a theoretical model can estimate the covariance matrix of the dataset. PLS-SEM is primarily used to develop theories in exploratory research with a focus on explaining the variance in the dependent variables when examining the model. Moreover, PLS-SEM makes no assumptions about the distribution of the data (e.g., normal distribution) and is superior compared to multiple regression which uses sum scores to calculate composite values (Hair et al., 2021). As such, PLS-SEM uses weighted composites of indicator variables facilitating accounting for measurement error. For these reasons, this research selected PLS-SEM to test the conceptual framework shown in Figure 2. The minimum sample size should safeguard the results of PLS-SEM to have adequate statistical power. When the maximum number of independent variables in the measurement and structural models is four, the sample size required is 41 to achieve a statistical power of 80% for detecting R^2 values of at least 0.25 at the 5% significance level (Hair et al., 2021). Finally, it is recommended to use "bootstrapping" to assess whether a path coefficient is significantly different from zero. The minimum number of bootstrap samples is 5,000 (Hair et al., 2021).

4.4 Case study description

The BLE system was set up in Project Alpha, a large residential project in Lima, during the structural works phase between August and September 2021. Project Alpha consists of five underground levels and nineteen stories with a structural frame of traditional *in-situ* reinforced concrete with structural components such as shear walls, columns, beams, and slabs. The typical floor plate of 1,100 m^2 has 12 apartments. The contractor has 19 years of experience in the market and has several subcontractors to execute the structural works. The site management team provided drawings, programmes, crew sizes, and the overall planning strategy. Four gateways were installed according to the project's zones. The gateways were placed in wooden boxes to protect them from weather and impact damage. These gateways were moved as the crews moved between zones and levels.

Before starting the monitoring process, all construction workers (N = 105) were briefed on the research protocol and invited to voluntarily participate in the study. Workers who accepted to participate in the study signed an informed consent agreement. This process was conducted according to Le Métayer and Monteleone's (2009) recommendations that the consent must be a) freely given, b) specific, and c) informed and unambiguous. Table 3 shows that 105 workers were invited to participate and 79 accepted being monitored. This is a participation rate of 75.2%. The monitoring process was conducted for 2 weeks per crew. First, the formwork installation crew participated in the study and was monitored during weeks 1 and 2 (N = 23). This was followed by the rebar installation crew who were monitored during weeks 3 and 4 (N = 18). The third crew who participated in the study were the bricklayers, who were monitored during weeks 5 and 6 (N = 17). Finally, a group of electricians, plumbers, and plasterers were monitored during weeks 7 and 8 (N = 21). At the end of the first

TABLE 3 Participants' summary.

Crew	Weeks	Invited	Accepted	N_1	N_2	Interviews
Formwork	1–2	30	23	16	14	3
Rebar	3–4	24	18	18	18	3
Bricklayers	5–6	26	17	14	13	3
Other	7–8	25	21	12	10	2
Total		105	79	60	55	11

TABLE 4 Demographics of construction workers at T_1.

Variable	Value	Frequency	Percentage
Skill	Skilled worker	35	58.3
	Non-skilled worker	25	41.6
Years of experience in construction	1–3 years	22	36.7
	4–6 years	17	28.3
	7–10 years	10	16.7
	More than 10 years	11	18.3
Crew	Rebar installation	18	30.0
	Formwork installation	16	26.7
	Bricklayer	14	23.3
	Plumber	4	6.7
	Electrician	4	6.7
	Plasterer	4	6.7

week (T_1), construction workers were invited to respond to the survey. However, some participants declined to fill out the survey. As a result, 60 responses were collected. At the end of the second week (T_2), the construction workers were invited again to respond to the same survey. As a result, 55 responses were collected. A summary of the construction workers who participated in this research is shown in Table 3. Therefore, the response rate was 75.9% and 69.6% for T_1 and T_2 respectively which was deemed to be acceptable for the nature of the study.

5 Quantitative stage

5.1 Participants' background

The demographics of the construction workers who agreed to fill out the survey at T_1 are shown in Table 4. Most participants had 1–6 years of experience in construction (65%) whilst 18.3% of the sample had more than 10 years of experience. Furthermore, 58.3.% of the respondents were skilled workers, whereas 41.6% were non-skilled workers. Skilled workers are trained and experienced in material installation and equipment handling for their specific tasks, whilst the non-skilled workers do contributory activities such as transport, moving materials, or cleaning.

5.2 Measurement validation

Two measurement models for T_1 and T_2 were estimated using Smart PLS4. The results are indicated in Table 5. First, all factor loadings were above the recommended threshold of 0.70 except for PS1 (T_1) and SF3 (T_2). Second, all latent factors' CR were above 0.7 and all AVEs are well above 0.5. Hair et al. (2021) recommended that indicators with loadings between 0.4 and 0.7 should be considered for removal from the scale only when deleting the indicator leads to an increase in the CR or AVE above the accepted thresholds. Since all CRs and AVEs are well above the accepted thresholds, PS1 (T_1) and PU1 (T_2) were retained based on their contribution to content validity. Hence, the convergent validity of the measurement model was accepted. On the other hand, the square root of all AVE estimates from Table 5 was greater than the corresponding latent factors' correlation estimates in Tables 6, 7. Therefore, the discriminant validity of the measurement models was also accepted.

5.3 K-means clustering

The k-means clustering classification was conducted using SPSS 28.0 using the pooled dataset (N = 115) with the average sum of scores per latent factor. The Within-cluster Sum of Squares (WCSS) statistical approach was used to determine the optimal number of clusters "k". WCSS measures the sum of the squares of the distances of each item to

TABLE 5 Convergent validity of latent factors.

Latent factor	Variable	T_1			T_2		
		Loading	CR	AVE	Loading	CR	AVE
PU	PU1	0.831	0.915	0.730	0.732	0.897	0.686
	PU2	0.893			0.819		
	PU3	0.829			0.877		
	PU4	0.864			0.877		
PPR	PPR1	0.833	0.920	0.741	0.890	0.937	0.787
	PPR2	0.866			0.847		
	PPR3	0.902			0.879		
	PPR4	0.842			0.930		
PS	PS1	0.533	0.833	0.562	0.912	0.917	0.734
	PS3	0.781			0.770		
	PS4	0.822			0.870		
	PS5	0.822			0.867		
SF	SF1	0.955	0.926	0.807	0.925	0.895	0.743
	SF2	0.918			0.952		
	SF3	0.816			0.683		
ATT	ATT1	0.832	0.878	0.706	0.971	0.840	0.640
	ATT2	0.864			0.973		
	ATT3	0.825			0.944		
INT	INT1	0.908	0.955	0.876	0.888	0.974	0.927
	INT2	0.958			0.831		
	INT3	0.940			0.663		

TABLE 6 Discriminant validity of latent factors (T_1).

Latent factor	ATT	INT	PPR	PS	PU	SF
ATT	0.840					
INT	0.783	0.936				
PPR	−0.446	−0.463	0.861			
PS	−0.401	−0.330	0.049	0.749		
PU	0.511	0.350	−0.394	−0.108	0.855	
SF	0.306	0.246	−0.182	0.213	0.327	0.898

Note: Values below the diagonal are correlation estimates between constructs, and values in the are the square root of AVE's.

the cluster centroid. The WCSS values for different values of "k" were compared to identify the point at which the drop in WCSS was no longer substantial. The analysis revealed that k = 2 was the optimal number of clusters for the data, indicating that the observations in the dataset could be divided into two distinct clusters based on their similarities in terms of the variables used in the analysis. An ANOVA analysis per cluster (Table 8) further confirmed this finding, showing a significant difference between the means of both groups, except for SF.

The two groups can be described as follows:

- Cluster 1 (*Supporters*): This cluster contains approximately 37% of the observations in the dataset. Workers in this cluster have relatively high scores in attitude, intention, and perceived usefulness whilst very low scores for perceived privacy risk and perceived stress, indicating a positive attitude towards the technology.

TABLE 7 Discriminant validity of latent factors (T_2).

Latent factor	ATT	INT	PPR	PS	PU	SF
ATT	0.800					
INT	0.822	0.963				
PPR	−0.819	−0.683	0.887			
PS	−0.227	−0.335	0.194	0.857		
PU	0.513	0.494	−0.487	−0.253	0.828	
SF	−0.428	−0.410	0.445	0.600	0.012	0.862

Note: Values below the diagonal are correlation estimates between constructs, and values in the are the square root of AVE's.

TABLE 8 ANOVA results per group.

Factor	Cluster 1		Cluster 2		ANOVA according to cluster	
	Mean	Standard deviation	Mean	Standard deviation	*F-value*	*p-value*
PPR	1.59	0.51	2.20	0.42	48.410	0.000
PU	3.30	0.47	2.72	0.41	49.715	0.000
PS	1.58	0.44	2.04	0.31	46.765	0.000
SF	2.14	0.70	2.27	0.42	1.682	0.197
ATT	3.34	0.37	2.63	0.44	76.975	0.000
INT	3.37	0.41	2.62	0.52	66.218	0.000

- Cluster 2 (*Acceptance with reservations*): This cluster contains approximately 63% of the observations in the dataset. Workers in this cluster have relatively average scores in attitude, intention, and perceived usefulness and average scores for perceived privacy risk and perceived stress, indicating a more negative or cautious attitude towards the technology.

Finally, data were cross tabulated to examine changes in worker groups between T_1 and T_2, as shown in Figure 4. The results revealed that 12 workers (24%) supported the system in both T_1 and T_2, whilst 25 workers (51%) remained in the acceptance with reservations cluster in both periods. Six workers (12%) shifted from cluster 1 to cluster 2 between T_1 and T_2, and an additional 6 workers (12%) moved from cluster 2 to cluster 1 during the same timeframe. These findings suggest that worker perceptions changed over time, which may have significant implications for the factors that influence technology adoption, as discussed in the following section. Specifically, the data reveals a degree of uncertainty and hesitation among most workers, indicating a need for further investigation into the reasons behind this attitude and potential socio-technical strategies to address it.

5.4 Structural equation modelling

In the previous section, CCA was presented to assess the validity of measured variables in the questionnaire and the underlying factors. In this section, paths will be added to the CCA models to conduct PLS-SEM. Data were analysed using Smart PLS 4 using 5,000 bootstrap samples. Table 9 presents the structural equation model results. First, models 1, 3, and 5 present the results with the control variables (years of professional experience and skill). Second, the predictors of the theoretical framework are added in models 2, 4, and 6. R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can be described as substantial, moderate, or weak, respectively (Hair et al., 2021). At T_1, the explained variance for "Attitude" and "Intention" is $R^2 = 0.532$ and $R^2 = 0.624$, suggesting that the variance explained by the theoretical framework is between moderate and substantial. The model suggests that "Perceived Usefulness" is associated with attitude towards monitoring systems ($\beta = 0.307$, $p < 0.05$). Therefore, hypothesis 1 was supported. Moreover, "Perceived Privacy Risk" was not found to be associated with attitude towards monitoring systems ($\beta = -0.248$). Hence, hypothesis 2 was not supported. Furthermore, there is a strong association between "Perceived Stress" and attitude towards monitoring systems ($\beta = -0.402$, $p < 0.001$). Therefore, hypothesis 3 is also supported. However, there is no evidence of a direct association between "Social Factors" with attitude towards monitoring systems ($\beta = 0.224$). Hence, hypothesis 4 was not supported. Finally, there is a strong association between attitude towards monitoring systems and intention to accept monitoring systems ($\beta = 0.800$, $p < 0.001$). Hence, hypothesis 5 was supported.

At T_2, the explained variance for "Attitude" and "Intention" is $R^2 = 0.713$ and $R^2 = 0.711$, suggesting that the variance explained by the theoretical framework is substantial. The model suggests that

	Support (T_2)	Reservations (T_2)	No data (T_2)
Support (T_1)	12	6	3
Reservations (T_1)	6	25	8
No data (T_1)	4	2	0

FIGURE 4
Cross tabulation of workers per cluster at T_1 and T_2.

TABLE 9 PLS-SEM results (5000 bootstrap samples).

	T_1		T_2		Pooled	
Model factors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent variable: INT						
Experience	−0.008	0.101	−0.118	−0.034	−0.056	0.036
Skill	0.200	−0.264	0.148	−0.200	0.238	−0.233
ATT	-	0.800^{a}	-	0.837^{a}	-	0.816^{a}
Dependent variable: ATT						
Experience	−0.102	−0.014	−0.089	0.005	−0.103	−0.011
Skill	0.581	0.351	0.470	0.154	0.488^{c}	0.248
PU	-	0.307^{c}	-	0.191	-	0.266^{c}
PPR	-	−0.248	-	-0.642^{a}	-	-0.446^{a}
PS	-	-0.402^{a}	-	0.026	-	-0.203^{c}
SF		0.224		−0.160		0.037
R^2 ATT	0.050	0.532	0.036	0.713	0.043	0.486
R^2 INT	0.027	0.624	0.018	0.711	0.010	0.672

Note: $^{a}p<0.001$; $^{b}p<0.01$; $^{c}p<0.05$. Standardised coefficients are reported. Sample size T_1 = 60; T_2 = 55; Pooled = 115.

"Perceived Usefulness" was not associated with attitude towards monitoring systems. Therefore, hypothesis 1 was not supported. Furthermore, there is a strong association between "Perceived Privacy Risk" with attitude towards monitoring systems ($\beta = -0.642$, $p < 0.001$). Hence, hypothesis 2 was supported. Moreover, "Perceived Stress" and "Social Factors" are found not to be associated with attitude towards monitoring systems. Therefore, hypotheses 3 and 4 were not supported. Finally, there is a strong association between attitude towards monitoring systems and intention to accept monitoring systems ($\beta = 0.837$, $p < 0.001$). Hence, hypothesis 5 was supported.

A pooled dataset was also examined following the suggestion of the seminal work of Venkatesh et al. (2003). The explained variance for "Attitude" and "Intention" is $R^2 = 0.486$ and $R^2 = 0.672$, suggesting that the variance explained by the theoretical framework is moderate. The model suggests that "Perceived Usefulness" is associated with attitude towards monitoring systems ($\beta = 0.266$, $p < 0.05$). Therefore, hypothesis 1 was supported. Furthermore, there is a strong association between "Perceived Privacy Risk" with attitude towards monitoring systems ($\beta = -0.446$, $p < 0.001$). Hence, hypothesis 2 was supported. Moreover, there is a strong association between "Perceived Stress" and attitude towards monitoring systems ($\beta = -0.203$, $p < 0.05$). Therefore, hypothesis 3 is also supported. However, there is no evidence of a direct association between "Social Factors" with attitude towards monitoring systems. Hence, hypothesis 4 was not supported. Finally, there is a strong association between attitude towards monitoring systems and intention to accept monitoring systems ($\beta = 0.816$, $p < 0.001$). Hence, hypothesis 5 was supported.

Further, retrospective *post hoc* analysis was conducted to assess the suitability of the final sample size for PLS-SEM. Kock and Hadaya (2018) proposed the use of the *inverse square root method* which considers the probability that the ratio of the lowest path coefficient and its standard error will be greater than the critical value of a test statistic for a specific significance level. Therefore, the results of the required minimum sample size depend only on one path coefficient and do not depend on the size of the most complex regression in the model (Hair et al., 2021). The significant coefficient for T_1 ranges between 0.307 and 0.800 whilst for T_2 ranges between 0.642 and 0.837. Using the inverse square root method, the minimum sample size for path

TABLE 10 Summary of hypotheses testing.

Hypothesis	T_1	T_2	Pooled
H1: PU → ATT	Accepted	Rejected	Accepted
H2: PPR → ATT	Rejected	Accepted	Accepted
H3: PS → ATT	Accepted	Rejected	Accepted
H4: SF → ATT	Rejected	Rejected	Rejected
H5: ATT → INT	Accepted	Accepted	Accepted

coefficients ranging between 0.31 and 0.40 and a power of 80% at the 5% significance level is 39 samples (Hair et al., 2021). Thus, the sample meets the requirements for analysis and interpretation using PLS-SEM. Table 10 presents a summary of the hypotheses testing.

6 Qualitative stage

Follow-up semi-structured interviews were conducted with a group of workers to provide a better understanding of the socio-technical aspects associated with technology acceptance. Thematic analysis was chosen as the qualitative data analysis technique to complement quantitative outcomes. Three crew members per team were invited for an interview and eleven workers consented to participate. Transcriptions of recorded data revealed four interrelated prevailing themes. First, job loss fear was strongly perceived by workers at the beginning but reduced towards the end of monitoring. Second, some workers believed that productivity levels on site are already known by all crews and therefore making use of a monitoring system would only reveal to site managers what is common knowledge amongst workers. Third, the acceptance of the system by workers would increase if they do not perceive any hindrance to their free movement or remain unaware of the presence of beacons. Moreover, a location-tracking system that facilitates safety management would gain more acceptance from workers. These results enrich quantitative outcomes and lend significance to factors and associations within the theoretical framework.

At first, some workers expressed concerns about the possibility of losing their jobs due to the perception that the company was targeting less productive employees, or that the data would be used to terminate their contracts. An interviewee claimed that those who declined to participate in the study viewed monitoring systems as a tool for *control* and *exploitation*. Despite this, 79 out of 105 workers accepted to be monitored, indicating an initial rejection rate of 24.7%. However, some of the monitored workers reported feeling more comfortable with the system as time went on. Initially, perceived stress, particularly the fear of job loss, strongly influenced workers' attitudes toward the system, but this diminished towards the end of the monitoring process, consistent with the study's quantitative results. Motivated workers appeared to be more accepting of the system than those who declined to participate. One worker stated that they loved their job and were honest, so the system did not affect them. These findings suggest that perceived stress, specifically the fear of losing one's job, initially had a significant impact on workers' acceptance of the monitoring system, but this declined over time.

Additionally, some workers argued that the monitoring system would rightly expose the less productive colleagues, for example, by tracking their breaks or naps in the bathroom or canteen. Moreover, other workers pointed out that daily tasks and productivity targets are transparent among the crews, and as long as they meet those targets, they have no reason to worry about being monitored. In fact, some workers even welcomed the idea of being observed, seeing it as a way to detect timewasters and improve productivity. These insights reflect social aspects within the project context. Furthermore, the beacons used for monitoring were provided to workers in armbands, but some workers found them uncomfortable or worried about the beacons falling and getting damaged. This suggests that for a large-scale monitoring system to be successful, beacons or sensors must be designed in a way that does not interfere with workers' movement and that they go unnoticed as much as possible.

Finally, some workers contended that they would support the real-time location system as a standard industry practice if it proved useful for safety management. Health and safety procedures impose a duty of care on crew members who must not leave their colleagues alone in dangerous areas. For instance, one worker stated that *"If you send your co-worker to the basement to get some materials, or if they go alone for any reason, and something happens, we will know where they are."* Another worker added, *"If I had an accident, they would locate me quickly and provide assistance."* Therefore, these findings suggest that the ease of locating workers in emergencies is another aspect of "Perceived Usefulness" associated with workers' acceptance of the monitoring system.

7 Discussion

7.1 Technology acceptance

Examining workers' reactions to location-tracking technologies for productivity monitoring has received little attention in the existing literature. Thus, extracting construction workers' perception of location-tracking technologies is a novel contribution. This study has examined workers' reactions to a real-time location monitoring system by adapting the Technology Acceptance Model (TAM). Over 2 weeks, workers who had no previous experience with monitoring were studied. Out of 105 workers who received induction, 24.7% refused to participate. This could be due to distrust or insecurity with the new system, insufficient information, and opposition to monitoring systems. The analysis of the data found that workers' attitude and intention to accept monitoring systems at the beginning of the monitoring process were linked to their perception of usefulness and stress. However, at the end of the process, the most significant factor influencing acceptance was their perception of privacy risk. Previous research has found that "Perceived Privacy Risk" is a barrier to the acceptance of wearable biosensors such as smart vests in construction (Choi et al., 2017), fitness devices (Gao et al., 2015), and digital personal health record systems (Li et al., 2014). Also, "Perceived Usefulness" was found to be positively associated with the intention to use personal protection equipment (Wong et al., 2021), wristbands (Choi et al., 2017), and healthcare wearables (Singh et al., 2022). Although previous studies provide insight into the acceptance of sensing technologies for health and safety, the present study focuses on real-time location tracking technology for productivity measurement. The study also found that "Social Factors" was not associated with attitude or intention. However, a similar factor (e.g., "Social Influence" or "Social Norm") was found associated with intention in previous studies in occupational health and safety (Gao et al., 2015; Choi et al., 2017; Wong et al., 2021). "Social Factors" was strongly correlated with "Perceived Privacy Risk" and "Perceived Stress" in T_2, with a correlation coefficient of 0.445 and 0.600, respectively. These findings suggest that "Social Factors" precedes "Perceived Privacy Risk" and "Perceived Stress", and as a result, the socio-technical implications must be further elucidated.

Qualitative interviews have shown that initially, workers had limited knowledge of the real-time location monitoring system and relied solely on the information provided during induction. They believed that the system would enhance productivity, logistics, and work quality. However, as they became more familiar with the system, they realised that its primary utility was in managing safety, as it could provide valuable assistance in case of an emergency. This finding indicates that location monitoring technologies designed to measure productivity could be integrated with sensing devices used for health and safety, which could increase the acceptance of such systems (Gao et al., 2015). Furthermore, workers experienced "Perceived Stress" due to the added pressure of potentially losing their jobs as a result of continuous monitoring of their location by site management. This made them more cautious about their movements and interactions with others. However, at T_2 workers experienced less stress and worry about losing their jobs compared to T_1, as indicated by the coefficients in Table 9.

Qualitative interviews have also indicated that workers and foremen already have knowledge of which workers are the most (and least) productive, and this information can potentially affect workers' willingness to participate in the location-tracking process. Therefore, some workers may approve of the monitoring system revealing the less productive workers to the site management team. However, those who are less productive may be less likely to accept such a transparent system. Additionally, there is a risk of incorrectly equating low-productive workers with those who do not accept the system, as some workers may not genuinely accept the technology. As a result, site managers should be transparent with the workforce, informing them of the data that will be collected and how it will be interpreted, analysed, and utilised. Finally, some workers also experienced discomfort while carrying the beacons, which impacted their daily productivity. The acceptance of monitoring systems relies on a non-obstructive method for locating the beacons such as attaching beacons to helmets or integrating them with ID badges.

7.2 Socio-technical implications

The study brings forward three key sociotechnical implications for construction firms when considering rolling out automated location tracking systems for productivity monitoring. The issues revolve around the nature of workers as social actors with technological frames that can change, the evolutionary nature of these technological frames as part of the journey towards acceptance, and the need for organisations to adopt management strategies that encompass collective problem identification and solutions. The identified non-technical factors complement existing insights about the take up and application of technology in several sectors (Oesterreich and Teuteberg, 2019), including construction (Shojaei and Burgess, 2022).

First, critical to technology acceptance is how construction workers will embrace it when rolled out. Therefore, identifying their perceptions related to acceptance is important. Concomitant to this is an understanding of how this acceptance may occur over time. Primary to this insight is the awareness presented from the qualitative study that workers are social actors who share frames of reference about technological artefacts, and that can change. From the findings, some workers fully supported the system and others supported it with reservations. Those who supported totally agreed with and would further support the use of the system. They also had high perceived usefulness of the technology and very low perceived privacy risks and stress about the technology. Workers who held reservations did not wholly accept the technology and were not completely convinced about the usefulness of the technology. They also held more potential privacy risks and stress levels that the system could pose. These frames of reference for the workers however evolve, as 24% of workers supported the system in Time 1 and Time 2 whilst 12% moved from support to acceptance with reservations. Similarly, 51% of workers accepted the system (with reservations) in Times 1 and 2 whilst 12% moved from acceptance with reservations to support. These shifts suggest that how groups of workers perceived the technological system changed over time, and the "how" should be of interest to the management of construction firms seeking to implement automated location tracking technology for productivity monitoring.

Second, workers are not merely those who "accept" or "rebel" by default. As social actors, they can make informed decisions so their perceptions, concerns and problems identified can be managed positively. This insight is crucial for the development of management approaches to aid the transition of workers who have reservations, to those who fully support the implementation of a technology. This can be achieved by identifying the rallying factors for workers who are "supporters" and using that to inform strategies for addressing the concerns or problems raised by those who identify issues with sensor-based data-gathering technology. For instance, the fear of job loss was strongly felt by workers at the beginning of the monitoring process, but these feelings appeared to have reduced at the end of the monitoring process. This ease potentially contributed to an increase in the percentage of workers who were supportive of the system. How that occurred is a useful question for the management of construction firms to note. Here, we argue that a problem-solution engagement between management and workers in construction firms is fundamental for addressing any perceived problems about technology (e.g., fear of job losses) to rally more support around its use.

The final sociotechnical observation from the study is about technology co-development and contextual considerations. It is common to find techno-centric studies making assumptions that suggest that technological systems are context-agnostic. However, from a sociotechnical viewpoint, the design and use of technology are significantly influenced by context. From the findings, workers would accept the system further if the beacons are unnoticeable and do not interfere with their free movement. In this case, the views of the workers and the kind of work they do means a preference for non-intrusive or non-obstructing technologies. This brings forward the need to consider such social (human-centric) needs as part of selecting and rolling out sensor-based automated data-capturing devices on construction sites and underscores the importance of establishing co-creative approaches for the design and implementation of systems that would require either or both parties to interact with a technological component. It is therefore plausible to argue that automated data capturing technology roll outs should consider concerns about how they could be made non-intrusive or non-obstructing technologies for successful implementation.

7.3 Managerial implications

Together, the findings of this study suggest that managerial teams should be aware of and work on workers' privacy risks, perceived stress, and perceived usefulness. As such, the first step for a full-scale roll out of the system is to ensure worker's and unions' buy-in and communication is key. The narratives to promote workers' acceptance would include: 1) location data will not be used for individual tracking but to understand crews' logistics and needs and to identify improvement areas; 2) location data can be also used for safety management; and 3) the technology is designed to go unnoticed by workers as much as practical. However, companies must also be aware of the potential risk of being sued by workers and unions due to the lack of regulations surrounding data privacy in monitoring systems within the construction sector.

The presence of workers outside their designated areas can offer opportunities for logistics and planning improvements since field-level issues often go unnoticed by site management (Halttula and Seppänen, 2022). Furthermore, encouraging the participation of workers and subcontractors in collaborative planning meetings may have a positive impact on the perceived usefulness of the monitoring system, and ultimately improve its acceptance. To achieve this, it is imperative to communicate the system as a tool for improving construction flows rather than a surveillance system that rewards or punishes workers. Workers should be able to see that their feedback is incorporated into the system to improve their work environment. Therefore, this approach can lead to productivity improvements for workers, subcontractors, and contractors.

The acceptance of technology in the construction industry is also influenced by power dynamics between contractors, subcontractors, and workers. Jandl et al. (2021) argued that workers' consent to provide location data to employers is not entirely voluntary, and agreements, either formal or informal, should be made clear. This creates a dilemma between mandating the system and asking workers to willingly participate. The study suggests that the system must not be mandatory. However, managers can consider the use of incentives to promote acceptance, with the caveat that these incentives should be focused on encouraging participation rather than rewarding individual results. Furthermore, since construction workers may not have permanent jobs, especially trade contractors who are appointed on a project-by-project basis, those with stable contracts and knowledge of the organisational culture may be more willing to accept the system. For example, they may trust the organisation and better understand that the monitoring system is for performance improvement rather than surveillance. Managers should create win-win environments where workers can see the benefits of the monitoring process for production planning and control.

8 Conclusion

The objective of this study was to explore how construction workers perceive and accept real-time location tracking technology for productivity monitoring, and the socio-technical implications. A radio-based monitoring system was deployed to track the location of workers during the structural phase of a large residential building, and a modified Technology Acceptance Model was developed to test workers' attitudes and intentions towards the monitoring system. Data were collected through questionnaires and semi-structured interviews conducted at two points during the monitoring process. The study found that workers' perceptions of usefulness and stress were significant predictors of their attitudes and intentions towards the monitoring system. However, perceived privacy risk emerged as the most important factor affecting workers' acceptance of the technology. Workers initially feared that the monitoring system could be used against them, but over time, they saw its potential benefits, such as locating workers in emergencies and improving productivity. The study suggests that monitoring technologies should not be used to evaluate workers' social behaviour but rather to find opportunities for productivity and safety improvement which helps both workers and employers. The research provides insights into workers' perceptions of monitoring technologies in the construction sector and highlights the importance of considering workers' wellbeing in the implementation of digitalisation in construction. The study underscores how critical to technology acceptance is the management of employee perceptions. We should move beyond rigid categorisations of workers into supporters and opposers and understand that views can be modified. The key to changing the views is understanding the underlying factors of opposition and reframing the usefulness of technology to address any concerns. These findings draw attention to the need to adopt a comprehensive approach to introducing and using new technologies in organisations and project settings.

The study has some limitations. Firstly, the results only apply to the specific case study, although case studies are designed to generalise to theoretical propositions as opposed to populations (Yin, 2014). Therefore, the results provide a rich understanding of the significant factors that affect workers' acceptance of technology. Secondly, future studies may require multiple case studies as location monitoring technologies become more widely used. Thirdly, a more extended monitoring period would have been preferable, but limited resources and the desire to reduce discomfort to workers made 2 weeks the best option. In the future, studies could monitor workers for longer periods and use different radio-based or vision-based techniques. Finally, the results may have been influenced by the specific project under study and the cultural and cognitive elements of a developing country. To confirm or challenge the findings of this research, future studies could replicate the method elsewhere.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

DM: Conceptualization, Formal Analysis, Investigation, Methodology, Writing–original draft, Writing–review and editing. AU: Conceptualization, Formal Analysis, Investigation, Methodology, Writing–original draft. JZ: Investigation, Writing–review and editing. KO-S: Formal Analysis, Writing–original draft, Writing–review and editing. OS: Writing–review and editing. XB: Writing–review and editing.

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Conflict of interest

Author JZ was employed by the company Solita Oy.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Abbe, O. O., Harvey, C. M., Ikuma, L. H., and Aghazadeh, F. (2011). Modeling the relationship between occupational stressors, psychosocial/physical symptoms and injuries in the construction industry. *Int. J. Ind. Ergon.* 41, 106–117. doi:10.1016/J.ERGON.2010.12.002

Ahn, C. R., Lee, S., Sun, C., Jebelli, H., Yang, K., and Choi, B. (2019). Wearable sensing technology applications in construction safety and health. *J. Constr. Eng. Manag.* 145. doi:10.1061/(asce)co.1943-7862.0001708

Alsulami, H., Serbaya, S. H., Rizwan, A., Saleem, M., Maleh, Y., and Alamgir, Z. (2021). Impact of emotional intelligence on the stress and safety of construction workers' in Saudi Arabia. *Eng. Constr. Archit. Manag.* 30, 1365–1378. doi:10.1108/ECAM-06-2021-0481

Awolusi, I., Marks, E., and Hallowell, M. (2018). Wearable technology for personalized construction safety monitoring and trending: review of applicable devices. *Autom. Constr.* 85, 96–106. doi:10.1016/j.autcon.2017.10.010

Baka, A., Figgou, L., and Triga, V. (2012). "Neither agree, nor disagree": a critical analysis of the middle answer category in Voting Advice Applications. *Int. J. Electron. Gov.* 5, 244–263. doi:10.1504/IJEG.2012.051306

Barbosa, F., Woetzel, J., Mischke, J., Ribeirinho, M., Sridhar, M., Parsons, M., et al. (2017). *Reinventing construction through a productivity revolution.* New York: McKinsey and Company.

Bergek, A., Hekkert, M., Jacobsson, S., Markard, J., Sandén, B., and Truffer, B. (2015). Technological innovation systems in contexts: conceptualizing contextual structures and interaction dynamics. *Environ. Innov. Soc. Transit* 16, 51–64. doi:10.1016/J.EIST.2015.07.003

Bowen, P., Edwards, P., Lingard, H., and Cattell, K. (2014). Workplace stress, stress effects, and coping mechanisms in the construction industry. *J. Constr. Eng. Manag.* 140. doi:10.1061/(asce)co.1943-7862.0000807

Cai, J., and Cai, H. (2020). Robust hybrid approach of vision-based tracking and radio-based identification and localization for 3D tracking of multiple construction workers. *J. Comput. Civ. Eng.* 34. doi:10.1061/(asce)cp.1943-5487.0000901

Celebi, M. E., Kingravi, H. A., and Vela, P. A. (2013). A comparative study of efficient initialization methods for the k-means clustering algorithm. *Expert Syst. Appl.* 40, 200–210. doi:10.1016/j.eswa.2012.07.021

Choi, B., Hwang, S., and Lee, S. H. (2017). What drives construction workers' acceptance of wearable technologies in the workplace? indoor localization and wearable health devices for occupational safety and health. *Autom. Constr.* 84, 31–41. doi:10.1016/j.autcon.2017.08.005

Creswell, J. W. (2014). *Research design: qualitative, quantitative, and mixed methods approaches.* California: SAGE Publications. Available at: https://books.google.co.uk/books?id=4uB76IC_pOQC.

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *Int. J. Man. Mach. Stud.* 38, 475–487. doi:10.1006/IMMS.1993.1022

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Manage Sci.* 35, 982–1003. doi:10.1287/mnsc.35.8.982

Dennerlein, J. T., Eyllon, M., Garverich, S., Weinstein, D., Manjourides, J., Vallas, S. P., et al. (2021). Associations between work-related factors and psychological distress among construction workers. *J. Occup. Environ. Med.* 63, 1052–1057. doi:10.1097/JOM.0000000000002311

Farmer, M. (2016). *The farmer review of the UK construction labour model: modernise or die.* London: construction leadership council.

Fishbein, M., and Ajzen, I. (1975). *Belief, attitude, intention, and behavior: an introduction to theory and research.* Boston: Addison-Wesley Publishing Company. Available at: https://books.google.co.uk/books?id=8o0QAQAAIAAJ.

Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* 18, 39–50. doi:10.1177/002224378101800104

Gao, Y., Li, H., and Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Manag. Data Syst.* 115, 1704–1723. doi:10.1108/IMDS-03-2015-0087

Geels, F. W., and Kemp, R. (2007). Dynamics in socio-technical systems: typology of change processes and contrasting case studies. *Technol. Soc.* 29, 441–455. doi:10.1016/J.TECHSOC.2007.08.009

Gefen, D., Rigdon, E. E., and Straub, D. (2011). Editor's comments: an update and extension to SEM guidelines for administrative and social science research. *MIS Q.* 35. iii–xiv. doi:10.2307/23044042

Hair, J. F., Hult, G. T. M., Ringle, C., and Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM).* California: SAGE Publications.

Hair, J. F., Ringle, C. M., and Sarstedt, M. (2011). PLS-SEM: indeed a silver bullet. *J. Mark. Theory Pract.* 19, 139–152. doi:10.2753/MTP1069-6679190202

Halttula, H. P. I., and Seppänen, O. (2022). "Situational awareness in construction projects using takt production," in 30th Annual Conference of the International Group for Lean Construction (IGLC), Edmonton, Canada, 25-31 July 2022, 164–174. doi:10.24928/2022/0119

Harty, C. (2005). Innovation in construction: a sociology of technology approach. *Build. Res. Inf.* 33, 512–522. doi:10.1080/09613210500288605

Hasan, S., and Sacks, R. (2023). Integrating BIM and multiple construction monitoring technologies for acquisition of project status information. *J. Constr. Eng. Manag.* 149, 04023051. doi:10.1061/JCEMD4.COENG-12826

Hellhammer, D. H., Stone, A. A., Hellhammer, J., and Broderick, J. (2010). "Measuring stress," in *Encyclopedia of behavioral neuroscience* (Amsterdam, Netherlands: Elsevier Inc), 186–191. doi:10.1016/B978-0-08-045396-5.00188-3

Huang, Y., Trinh, M. T., and Le, T. (2021). Critical factors affecting intention of use of augmented hearing protection technology in construction. *J. Constr. Eng. Manag.* 147. doi:10.1061/(asce)co.1943-7862.0002116

Hwang, S., Jebelli, H., Choi, B., Choi, M., and Lee, S. (2018). Measuring workers' emotional state during construction tasks using wearable EEG. *J. Constr. Eng. Manag.* 144. doi:10.1061/(asce)co.1943-7862.0001506

Jandl, C., Wagner, M., Moser, T., and Schlund, S. (2021). Reasons and strategies for privacy features in tracking and tracing systems—a systematic literature review. *Sensors* 21, 4501. doi:10.3390/s21134501

Jebelli, H., Choi, B., and Lee, S. (2019). Application of wearable biosensors to construction sites. I: assessing workers' stress. *J. Constr. Eng. Manag.* 145. doi:10.1061/(asce)co.1943-7862.0001729

Kim, H., Ham, Y., Kim, W., Park, S., and Kim, H. (2019). Vision-based nonintrusive context documentation for earthmoving productivity simulation. *Autom. Constr.* 102, 135–147. doi:10.1016/J.AUTCON.2019.02.006

Kock, N., and Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: the inverse square root and gamma-exponential methods. *Inf. Syst. J.* 28, 227–261. doi:10.1111/isj.12131

Lagos, C., and Alarcón, L. (2021). Assessing the relationship between constraint management and schedule performance in Chilean and Colombian construction projects. *J. Manag. Eng.* 37, 04021046. doi:10.1061/(ASCE)ME.1943-5479.0000942

Le Métayer, D., and Monteleone, S. (2009). Automated consent through privacy agents: legal requirements and technical architecture. *Comput. Law Secur. Rev.* 25, 136–144. doi:10.1016/J.CLSR.2009.02.010

Li, H., Gupta, A., Zhang, J., and Sarathy, R. (2014). Examining the decision to use standalone personal health record systems as a trust-enabled fair social contract. *Decis. Support Syst.* 57, 376–386. doi:10.1016/j.dss.2012.10.043

Love, P. E. D., Edwards, D., and Irani, Z. (2010). Work stress, support, and mental health in construction. *J. Constr. Eng. Manag.* 136, 650–658. doi:10.1061/ASCECO.1943-7862.0000165

Luo, X., Li, H., Cao, D., Yu, Y., Yang, X., and Huang, T. (2018). Towards efficient and objective work sampling: recognizing workers' activities in site surveillance videos with two-stream convolutional networks. *Autom. Constr.* 94, 360–370. doi:10.1016/J.AUTCON.2018.07.011

Man, S. S., Alabdulkarim, S., Chan, A. H. S., and Zhang, T. (2021). The acceptance of personal protective equipment among Hong Kong construction workers: an integration of technology acceptance model and theory of planned behavior with risk perception and safety climate. *J. Saf. Res.* 79, 329–340. doi:10.1016/j.jsr.2021.09.014

Murguia, D., Chen, Q., Van Vuuren, T. J., Rathnayake, A., Vilde, V., and Middleton, C. (2022). Digital measurement of construction performance: data-to-dashboard strategy. *IOP Conf. Ser. Earth Environ. Sci.* 1101, 092009. doi:10.1088/1755-1315/1101/9/092009

Murguia, D., Vasquez, C., Demian, P., and Soetanto, R. (2023). BIM adoption among contractors: a longitudinal study in Peru. *J. Constr. Eng. Manag.* 149, 04022140. doi:10.1061/(asce)co.1943-7862.0002424

Nazareno, L., and Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technol. Soc.* 67, 101679. doi:10.1016/j.techsoc.2021.101679

Nnaji, C., and Awolusi, I. (2021). Critical success factors influencing wearable sensing device implementation in AEC industry. *Technol. Soc.* 66, 101636. doi:10.1016/j.techsoc.2021.101636

Oesterreich, T. D., and Teuteberg, F. (2019). Behind the scenes: understanding the socio-technical barriers to BIM adoption through the theoretical lens of information systems research. *Technol. Forecast Soc. Change* 146, 413–431. doi:10.1016/J.TECHFORE.2019.01.003

Okpala, I., Nnaji, C., and Awolusi, I. (2022). Wearable sensing devices acceptance behavior in construction safety and health: assessing existing models and developing a hybrid conceptual model. *Constr. Innov.* 22, 57–75. doi:10.1108/CI-04-2020-0056

Okpala, I., Nnaji, C., Awolusi, I., and Akanmu, A. (2021). Developing a success model for assessing the impact of wearable sensing devices in the construction industry. *J. Constr. Eng. Manag.* 147. doi:10.1061/(asce)co.1943-7862.0002064

Olivieri, H., Seppänen, O., and Peltokorpi, A. (2017). Real-time tracking of production control: requirements and solutions. *Lean Comput. Constr. Congr.* LC3, 671–678. doi:10.24928/2017/0177

ONS (2021). *Productivity in the construction industry*. UK: ONS, 2021.

Palaniappan, K., Natarajan, R., and Dasgupta, C. (2022). Prevalence and risk factors for depression, anxiety and stress among foreign construction workers in Singapore–a cross-sectional study. *Int. J. Constr. Manag.* 23, 2479–2487. doi:10.1080/15623599.2022.2070343

Paneru, S., and Jeelani, I. (2021). Computer vision applications in construction: current state, opportunities and challenges. *Autom. Constr.* 132, 103940. doi:10.1016/J.AUTCON.2021.103940

Park, Y., Son, H., and Kim, C. (2012). Investigating the determinants of construction professionals' acceptance of web-based training: an extension of the technology acceptance model. *Autom. Constr.* 22, 377–386. doi:10.1016/J.AUTCON.2011.09.016

PwC (2018). *BIM level 2 benefits measurement application of PwC's BIM level 2 benefits measurement methodology to public sector capital assets*. London, England: PwC.

Rao, A. S., Radanovic, M., Liu, Y., Hu, S., Fang, Y., Khoshelham, K., et al. (2022). Real-time monitoring of construction sites: sensors, methods, and applications. *Autom. Constr.* 136, 104099. doi:10.1016/j.autcon.2021.104099

Sacks, R., Brilakis, I., Pikas, E., Xie, H. S., and Girolami, M. (2020). Construction with digital twin information systems. *Data-Centric Eng.* 1, e14. doi:10.1017/dce.2020.16

Schweber, L., and Harty, C. (2010). Actors and objects: a socio-technical networks approach to technology uptake in the construction sector. *Constr. Manag. Econ.* 28, 657–674. doi:10.1080/01446191003702468

Shojaei, R. S., and Burgess, G. (2022). Non-technical inhibitors: exploring the adoption of digital innovation in the UK construction industry. *Technol. Forecast Soc. Change* 185, 122036. doi:10.1016/J.TECHFORE.2022.122036

Singh, N., Misra, R., Singh, S., Rana, N. P., and Khorana, S. (2022). Assessing the factors that influence the adoption of healthcare wearables by the older population using an extended PMT model. *Technol. Soc.* 71, 102126. doi:10.1016/j.techsoc.2022.102126

Son, H., Lee, S., and Kim, C. (2015). What drives the adoption of building information modeling in design organizations? An empirical investigation of the antecedents affecting architects' behavioral intentions. *Autom. Constr.* 49, 92–99. doi:10.1016/J.AUTCON.2014.10.012

Son, H., Park, Y., Kim, C., and Chou, J. S. (2012). Toward an understanding of construction professionals' acceptance of mobile computing devices in South Korea: an extension of the technology acceptance model. *Autom. Constr.* 28, 82–90. doi:10.1016/J.AUTCON.2012.07.002

Sony, M., and Naik, S. (2020). Industry 4.0 integration with socio-technical systems theory: a systematic review and proposed theoretical model. *Technol. Soc.* 61, 101248. doi:10.1016/J.TECHSOC.2020.101248

Teizer, J., Neve, H., Li, H., Wandahl, S., König, J., Ochner, B., et al. (2020). Construction resource efficiency improvement by long range wide area network tracking and monitoring. *Autom. Constr.* 116, 103245. doi:10.1016/J.AUTCON.2020.103245

Thompson, R. L., Higgins, C. A., and Howell, J. M. (1991). Personal computing: toward a conceptual model of utilization. *MIS Q.* 15, 125–143. doi:10.2307/249443

Umer, W. (2022). Simultaneous monitoring of physical and mental stress for construction tasks using physiological measures. *J. Build. Eng.* 46, 103777. doi:10.1016/j.jobe.2021.103777

Urbina, A. (2019). *Real-time monitoring of production in a construction project* Master's thesis Lima: Pontifical Catholic University of Peru.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Q.* 27, 425–478. doi:10.2307/30036540

Williams, R., and Edge, D. (1996). The social shaping of technology. *Res. Policy* 25, 865–899. doi:10.1016/0048-7333(96)00885-2

Wong, T. K. M., Man, S. S., and Chan, A. H. S. (2021). Exploring the acceptance of PPE by construction workers: an extension of the technology acceptance model with safety management practices and safety consciousness. *Saf. Sci.* 139, 105239. doi:10.1016/J.SSCI.2021.105239

Wu, R. W., Yiu, T. W., and Jelodar, M. B. (2022). "Real-time employee monitoring technologies in the construction sector - effect, readiness and theoretical perspectives: the case of New Zealand," in IOP Conference Series: Earth and Environmental Science (Institute of Physics). doi:10.1088/1755-1315/1101/8/082010

Wu, X., Kumar, V., Ross, Q. J., Ghosh, J., Yang, Q., Motoda, H., et al. (2008). Top 10 algorithms in data mining. *Knowl. Inf. Syst.* 14, 1–37. doi:10.1007/s10115-007-0114-2

Yin, R. K. (2014). *Case study research*. California, United States: SAGE Publications.

Zhang, B., Zhu, Z., Hammad, A., and Aly, W. (2018). Automatic matching of construction onsite resources under camera views. *Autom. Constr.* 91, 206–215. doi:10.1016/J.AUTCON.2018.03.011

Zhang, M., Shu, L., Luo, X., Yuan, M., and Zheng, X. (2022). Virtual reality technology in construction safety training: extended technology acceptance model. *Autom. Constr.* 135, 104113. doi:10.1016/j.autcon.2021.104113

Zhao, J., Seppänen, O., Peltokorpi, A., Badihi, B., and Olivieri, H. (2019). Real-time resource tracking for analyzing value-adding time in construction. *Autom. Constr.* 104, 52–65. doi:10.1016/j.autcon.2019.04.003

Zhao, J., Zheng, Y., Seppänen, O., Tetik, M., and Peltokorpi, A. (2021). Using real-time tracking of materials and labor for kit-based logistics management in construction. *Front. Built Environ.* 7. doi:10.3389/fbuil.2021.713976