Automated Progress Measurement Using Computer Vision Technology - Implementation in Construction

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Abstract

A critical concern with the UK's construction project progress monitoring and control techniques is their dependency on data collection, which is time-consuming and unproductive and may lead to various circumstances in managing projects. However, collecting and accurately analysing information from construction sites requires the development of technologies. As key AI technology, computer vision is a powerful tool for big data analysis which can address the above challenges. This study explores the status of CV-CPM adoption and the main barriers to and incentives for its adoption within UK construction sites. In this respect, after an extensive review of literature covering the AI technology in construction management, the concept, function, and usage of CV and its integration with CPM, including its benefits and drivers, and technical challenges, a questionnaire was administered to UK construction professionals to collect their perceptions. The study's results indicated that construction practitioners are relatively aware of CV-CPM but lack competencies and skills. CV-CPM has been perceived to be relatively better than the traditional approach. Implications like the cost of implementation, lack of expertise, and resistance to change were the major challenges in CV-CPM adoption. Instead, technological development, decision-making, and competitiveness were classified as incentives for its adoption.

Keywords: Project Management, Construction Management, Artificial Intelligence, UN SDG 9.

1. Introduction

Construction is perceived to be the largest economy in the UK; it donates almost £90b to the economy, equal to 6.7% in value-added, includes over 280,000 firms obscuring 2.93 million employments; hiring 3.1 million people or around 9% of the labour force (DBIS, 2013). However, many challenges have hindered growth and led to extremely low productivity levels compared with other industries (MGI, 2017). Many of these challenges are due to the sector remaining siloed and fragmented (CSIC, 2021) and relying on a labour-intensive business model, which has become unsustainable (DBEIS, 2019). Many processes have remained paper-based, information is not frequently optimised (CSIC, 2021), and eventually, reliance on manual data compilation negatively impacts site productivity and the control system, especially in controlling projects (Stilla, 2015). Some reports indicate that two-thirds of the sector fail to innovate (DBEIS, 2013). The deficiency in adopting digital technology has also been correlated to poor performance, decision-making, and cost inefficiencies and delays (Nikas *et al.*, 2007), making project management more complex and unnecessarily tedious (Delgado and Oyedele, 2021). As highlighted previously, achieving desired performance during construction is challenging (Golparvar-Fard *et al.*, 2009). The core problems are mainly sustaining the program, ensuring the supply chain, and monitoring and controlling the work status (Teizer, 2015). The current data collection method, irrespective of project scale, indoor or outdoor, is expensive, inaccurate, and inefficient (Golparvar-fard *et al.,* 2009). Deploying a proper method with timely feedback on project status assist PMs in determining the exact percentages of task completions and facilitating resource allocation (Teizer, 2015; Alizadehsalehi and Yitmen, 2019). The recent revolution in Artificial intelligence (AI), such as computer vision, has benefited this industry in many ways, enhancing productivity (MGI, 2017). CV allows a computer to see, describe, and understand the site's extracted data (IBM, 2022). Adopting such smart technology on-site is estimated to achieve 50% to 60% construction productivity (MGI, 2017).

CV-CPM is a new concept in the construction industry. Researchers have made several efforts to review various aspects of automating CPM with different techniques. However, the literature review of related academic references demonstrated that CV-CPM adoption had received limited attention. This study investigates the key challenges in implementing CV-CPM associated with the UK construction sector and then provides recommendations to mitigate these challenges. This study explores the status of CV-CPM adoption and the main barriers to and incentives for CV-CPM adoption within UK construction sites. The objectives include i. investigation of CV-CPM usage and advantages over traditional CPM approaches within UK construction sites, ii. Investigation of challenges to CV-CPM implementation within UK construction sites, and iii. Investigation of the possible incentives and drivers influencing CV- CPM implementation within UK construction Sites. The research further aimed to answer the questions including *a*. to what extent the construction professionals are familiar with CV-CPM, *b*. how construction professionals perceive CV-CPM over traditional methods, *c*. to what extent are they employing it, *d*. why they decide to use it (incentives) or why don't they use it (barriers), and *e*. what are the solutions to overcome the barriers and promote CV-CPM?

2. Literature Review

2.1 Diffusion of Innovation Theory (DIT)

This study uses Rogers's (2003) diffusion of innovation theory to determine the parameters influencing incentives and barriers to CV-CPM adoption. He describes the diffusion process as gradually transmitting innovation amongst the members of a social system via special channels. The author has identified innovations' characteristics: relative advantage, compatibility, complexity, trialability, and observability. In his opinion, *"innovations that individuals perceive as having a greater relative advantage, compatibility, trialability, observability and minor complexity will be adopted more rapidly than other innovations."* Therefore, the perceived aspects of the invention (CV-CPM) can help identify its adoption status. Complexity assumes the relative amount of effort required to use CV-CPM. Compatibility presumes the availability of experience and resources for potential adopters to adopt CV-CPM smoothly. Trialability refers to testing CV-CPM before utilising it and observability if the impacts of using CV-CPM are straightforward.

2.2 CPM and current status and the Role of AI technology

According to Acaster *et al.* (2017), monitoring and control play a crucial role in project management as they involve decision-making and aim to ensure that work is carried out according to program, resource, and cost plans while maintaining alignment with the business case. Monitoring involves the collection, recording, and reporting of project performance information (PMBOK GUIDE, 2021), allowing for the identification of lagging areas that require attention and action. However, inadequate and imprecise monitoring and tracking contribute to time and cost inefficiencies in projects (Ekanayake *et al.*, 2021; Omar *et al.*, 2018). The current manual data collection method is time-consuming, prone to errors, and negatively impacts data quality (Kiziltas and Akinci, 2005). Moreover, it introduces biases and creates a time lag between reported and actual progress (Mantel and Meredith, 2009; Golparvar-Fard *et al.*,2009; Golparvar-Fard *et al.*, 2011). Additionally, the visual complexity of the current methods fails to capture the spatial features of site progress and associated complexities (Koo and Fischer, 2000).

To address these challenges, the use of artificial intelligence (AI) has emerged as a transformative approach to implement digital strategies in project management (Pan and Zhang, 2021). AI enables computers to perceive, learn, and intelligently process inputs, similar to human capabilities, facilitating perception, knowledge modeling, logic, problem-solving, and planning (Thomas and Zikopoulos, 2020). By leveraging AI, project management processes can be made more technically automatable and accurate (Pan and Zhang, 2021). Advanced analytics derived from AI contribute to a deeper understanding of construction projects, standardizing implicit knowledge from project experiences, and enabling data-driven identification of project issues (Hu and Castro-Lacouture, 2019). Fig. 1. provides an illustration of the various AI applications in the construction industry. However, it is important to note that this study specifically focuses on computer vision applications due to the limitations of the research.

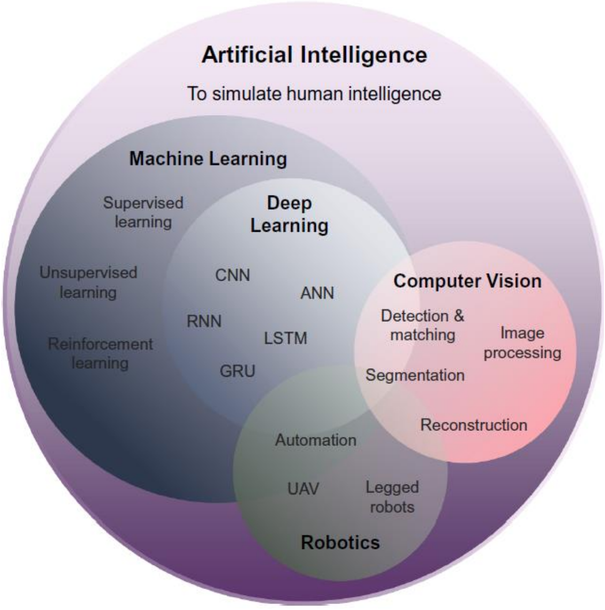


Fig. 1. AI types to simulate human intelligence include machine learning, deep learning, computer vision, and robotics and frequently used terminologies (source: Huang *et al.*, 2021)

2.3 The concept, function, and Integration of CV with CPM

This technology enables computers to analyse and extract meaningful information from images, videos, and other observable inputs, allowing them to make informed decisions. Artificial intelligence empowers machines to perceive and understand through computer vision (IBM, 2022). In the construction industry, with its abundance of visual data, the automatic extraction and analysis of this valuable information can bring significant benefits (Paneru and Jeelani, 2021). Figure 2 provides a visual representation of a typical computer vision pipeline in the context of construction.

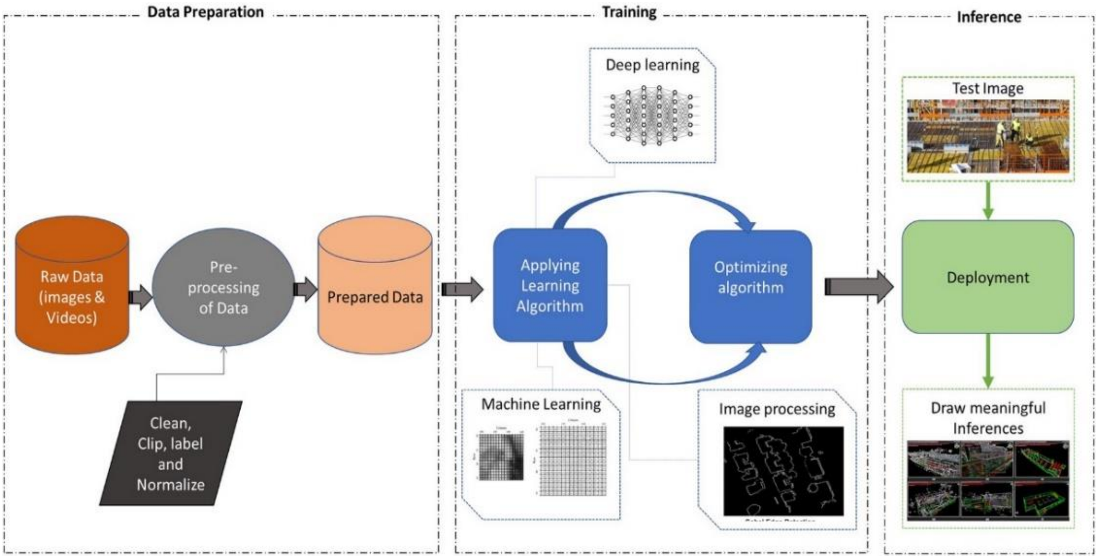


Fig. 2. A typical concept of a computer vision-based system (source: Paneru *et al.* 2021)

Computer vision (CV) has revolutionized progress monitoring by automating various tasks involved in the process (Paneru and Jeelani, 2021). It overcomes current challenges by tracing multiple entities within a camera view and extracting comprehensive information from images (Park *et al.*, 2011). This technology enables computers to derive numeric information from videos, depth images, and 3D point clouds, and process the data accordingly (Reja *et al.*, 2022). Various technologies, such as fixed, handheld, or robotic systems mounted on unmanned ground vehicles (UGV) or unmanned aerial vehicles (UAV), generate inputs through image frames or point clouds (Kopsida and Brilakis, 2020). The selection of these technologies depends on the desired level of automation for data capture (Reja *et al.*, 2022).

A recent study by Reja *et al.* (2022) proposed an integrated CV-CPM framework that combines various concepts and technologies to automate construction project management processes. Golparvar-Fard *et al.* (2009) conducted a trial project at the College of Business Instructional Facility, UIUC, where they examined and assessed schedule deviation using the as-planned as-built approach in a building project.

2.4 Benefits/Drivers, and Challenges to adoption

CV-CPM technology offers numerous benefits and drivers for its adoption in the construction industry. According to Reja *et al.* (2022), CV-CPM has the potential to provide real-time, accurate, and reliable information to construction managers, enabling them to make informed decisions. It offers a cost-effective solution for automated monitoring processes (Panahi *et al.*, 2022). Studies by Brilakis *et al.* (2011)

and Ekanayake *et al.* (2021) have shown that CV optimization improves the efficiency of construction work monitoring and tracking. It can also track the activities of plants and machinery to determine their efficiencies and impact on construction progress (Morgane *et al.*, 2022).

The use of CV-CPM allows for quick assessment through on-demand snapshots, aiding in the optimization of schedule and resource planning (Ibrahim *et al.*, 2009; Paneru and Jeelani, 2021). It offers accuracy, reliability, and transparency in project assessment (Ibrahim *et al.*, 2009). CV-CPM facilitates the early identification of project hindrances, enabling timely countermeasures (Braun and Borrmann, 2019). It allows planners to analyze project history for delays and react efficiently (Alizadehsalehi and Yitmen, 2019). With its high effectiveness in analyzing and quantifying site progress, CV-CPM reduces the need for manual monitoring and investigation, allowing project managers to focus on budget and time control (Teizer, 2015). It also aids in progress forecasting, simulation, and evaluation of control measures to bring the project back on track (Reja *et al.*, 2022).

The implementation of CV-CPM, particularly when integrated with Building Information Modeling (BIM), promotes automation and reduces the extent of human intervention (Morgane *et al.*, 2022). It provides a direct and fast input for capturing geometrical attributes (Reja *et al.*, 2022). By comparing digital images to geometric and material properties using machine learning algorithms, CV-CPM can automatically detect and determine significant changes on-site, assisting project managers and planners in better change control (Ibrahim *et al.*, 2009). Additionally, CV-CPM can provide visual and quantity details that can be utilized as evidence for contractual claims and early alerts on possible delays, supporting schedule and cost control (Zhang *et al.*, 2009; Reja *et al.*, 2022).

The advantages of CV-CPM can drive firms to be innovative and technologically advanced (Suprun and Stewart, 2015). Technological advancement is crucial for improving competitive advantage (Nam and Tatum, 1988). The desire for competitive advantage and competitiveness are significant drivers of innovation diffusion in construction companies (Johansson and Opseth, 2021; Sayfullina, 2010). Table 1 summarises other benefits of CV-CPM technology.

Table 1: Presents a summary of the other advantages of CV-CPM innovation:

Advantages	***Reference***
▪ Improved leadership and decision support systems	(Olatunji and Akanmu, 2014; Golparvar-Fard *et al.*, 2011; Zhang *et al.*, 2021)
▪ Save time and improve productivity	(Zhang *et al.*, 2021; Teizer, 2015)
▪ Better document quality	(Aghimien *et al.*, 2018; Zhang *et al.*, 2021)
▪ Process and performance improvement	(Ozorhon and Oral, 2017; Ibrahim *et al.*, 2009)
▪ Track equipment and material which affects the schedule	(Dimitrov and Golparvar-Fard, 2014; Teizer, 2015)
▪ Change detection	(Teizer, 2015; Fard and Peña-Mora, 2007)
▪ Lawsuit/dispute avoidance (Time wise)	(Teizer, 2015; Rebolj *et al.*, 2008)
▪ Transparency and accuracy	(Seo *et al.*, 2015)

CV-CPM has the potential to create a significant impact by providing real-time, accurate, and reliable information to construction managers (Reja *et al.*, 2022). It offers an inexpensive solution, depending on the technology, for automating monitoring processes (Panahi *et al.*, 2022). Researchers such as Brilakis *et al.* (2011) and Ekanayake *et al.* (2021) have found that using CV optimizes and increases the efficiency of construction work monitoring and tracking. It enables the tracking of activities of plants and machinery to determine their efficiencies and impact on construction progress (Morgane *et al.*, 2022). The consistent on-demand snapshots enable quick assessments (Ibrahim *et al.*, 2009) and facilitate optimized schedule and resource planning (Paneru and Jeelani, 2021). CV-CPM provides prompt and accurate assessment, enhancing accuracy, reliability, and transparency (Ibrahim *et al.*, 2009). It enables the early identification of project hindrances for timely countermeasures (Braun and Borrmann, 2019). Moreover, CV-CPM allows project planners to analyze project history for delays, conduct root cause analysis, and react efficiently (Alizadehsalehi and Yitmen, 2019).

The application of CV-CPM in construction automates diverse construction-related activities, aiding in the quantification of site progress and reducing the need for manual monitoring and investigation of progress status and performance by project managers (Teizer, 2015). It facilitates progress forecasting, simulation, and evaluation of control measures to bring projects back on track (Reja *et al.*, 2022). By reducing errors and rework, CV-CPM helps prevent time and cost deviations (Kopsida *et al.*, 2015). Integrating CV with Building Information Modeling (BIM) further automates processes and reduces the extent of human intervention, particularly in capturing geometrical attributes accurately and efficiently (Morgane *et al.*, 2022). The visual assessment provided by CV-CPM enables automatic detection and determination of significant changes on-site through the comparison of digital images with the geometric and material properties of components and activities using machine learning algorithms (Ibrahim *et al.*, 2009). This significantly assists project managers and planners in better change control. Furthermore, CV-CPM can provide visual and quantity details that can be utilized as evidence for potential contractual claims (Zhang *et al.*, 2009), as well as provide early alerts on possible delays, aiding in schedule and cost control (Zhang *et al.*, 2009).

The advantages of CV-CPM, such as updating schedules, generating reports/notifications, and progress quantification, can positively influence firms to adopt innovative approaches (Reja *et al.*, 2022). Technological advancement is crucial for companies seeking to improve their competitive advantage (Nam and Tatum, 1988). Competitiveness plays a significant role in the maturity of construction companies for CV-CPM innovation (Johansson and Opseth, 2021). The demand for competitive advantage among institutions drives innovation diffusion (Sayfullina, 2010). Table 1 summarizes the additional benefits of CV-CPM technology.

However, the adoption of CV-CPM in the construction industry is not without its challenges. These challenges can be categorized into technology, methodology, and individual factors, as identified by Odubiyi *et al.* (2019), or cost-related, process-related, and technology-related matters, as categorized by Sardroud (2015). The construction industry's dynamic nature and site complexities present specific challenges to implementing CV-CPM (Qureshi *et al.*, 2020). Stakeholders' perceptions, such as concerns about operating costs, lack of well-trained staff, and technology immaturity, can act as barriers to adoption (Arabshahi *et al.*, 2021). The initial cost of implementation is frequently cited as a major obstacle, along with hidden costs of training, maintenance, and operation (Alizadehsalehi and Yitmen, 2019; Goodrum *et al.*, 2011). Storing the large amount of data obtained from CV-CPM poses its own cost challenges (Martinez *et al.*, 2019). The dynamic and complex nature of the construction industry adds further risk to the cost of implementing new technology (Demirkesen and Tezel, 2021).

In addition to cost-related barriers, challenges related to individuals and their skills are also present. There may be a lack of interest and well-trained staff in embracing and utilizing innovative technologies (Singh *et al.*, 2011; Didehvar *et al.*, 2018). The fragmented nature of the construction sector contributes to low awareness and adoption of innovative approaches and technologies (Shen *et al.*, 2010; Evans and Heimann, 2022). The industry suffers from a lack of competency among construction workers and professionals (Oesterreich and Teuteberg, 2019). Lack of expertise and skills in using modern technologies can create doubts among managers and hinder the adoption of recent technologies (Hewage *et al.*, 2008; Doloi *et al.*, 2012). The unavailability of human resources with proficiency in computational areas in construction can also be a barrier to implementing CV-CPM (Morgane *et al.*, 2022). The construction sector's resistance to change and conservative nature pose significant challenges to the adoption of innovative technologies (Oesterreich and Teuteberg, 2016; Trstenjak and Cosic, 2017; Woodhead *et al.*, 2018). The implementation of CV-CPM requires process changes at all levels of the organization, which may encounter resistance due to the industry's historical reluctance to change (Young *et al.*, 2021).

Unclear benefits and returns on investment can contribute to the unwillingness to embrace change and invest in innovative technologies (Demirkesen and Tezel, 2021). Companies may be hesitant to adopt industry 4.0 and AI in construction due to uncertainties regarding the benefits in terms of cost savings and investment requirements (Zhou *et al.*, 2015; Oesterreich and Teuteberg, 2016; Dallasega *et al.*, 2018). Lack of client demand is another barrier, as reported by the SmartMarket report (2012), with a significant percentage of companies lacking requirements from clients for the adoption of automation technologies on project sites (Kassem *et al.*, 2012; Mitropoulos and Tatum, 2000). Lack of in-house expertise and clients' demand for technology adoption are cited as barriers to implementing innovative technologies (NBS, 2019; Eadie *et al.*, 2013; Vass and Gustavsson, 2017).

Table 2. Various Barriers identified to the adoption of CV-CPM.

Barriers	***References***	***Barriers***	***References***
operating cost	(Goodrum *et al.*, 2011)	lack of well-trained staff	(Akinbile and Oni, 2016)
cost of training and employing professionals	(Ahmed *et al.*, 2018)	legal or ethical concerns, privacy	(Häikiö *et al.*, 2020; Ball, 2010)
maintenance	(Dithebe *et al.*, 2019)	resistance to change	(Didehvar *et al.*, 2018)
cost of implementation	(Olaniyan, 2019)	company culture	(Adriaanse *et al.*, 2010)
uncertain cost-benefit relation	(Amusan Lekan *et al.*, 2018)	lack of government support (Lack of internal and external demand)	(Rogers *et al.*, 2015)
operational difficulties	(Jiang and Li, 2022)	change in the process	(Didehvar *et al.*, 2018)
data management issues	(Ahmed *et al.*, 2018)	site-related issues	(Golizadeh *et al.*, 2019)
technology immaturity	(Golizadeh *et al.*, 2019)	temporary nature of construction	(Adriaanse *et al.*, 2010)

Institutional constraints may hinder the adoption of CV-CPM. According to institutional theory, institutions undergo isomorphism through three forces: coercive, normative, and mimetic (Loosemore *et al.*, 2021; Cao *et al.*, 2014). Coercive isomorphism is driven by pressures from other organizations and the need to conform to societal expectations (DiMaggio & Powell, 1983). Contractors may feel compelled to change their methods when faced with new requirements from the public sector (Loosemore *et al.*, 2021). Normative isomorphism involves the development of shared norms within specific professional bodies. Mimetic isomorphism occurs when organizations imitate successful peers in the absence of clear courses of action (Mizruchi & Fein, 1999).

While CV-CPM holds theoretical feasibility, several computational issues still need resolution (Morgane *et al.*, 2022). Additionally, technical challenges such as integrity, durability, and reliability can impede the adoption of innovative technologies (Schall Jr *et al.*, 2018; Golizadeh *et al.*, 2019). Computer vision follows the principle of "what you see is what you can analyze," with data collection and analysis being the key steps in the process (Fang *et al.*, 2018a; Fang *et al.*, 2018b). Table 3, adapted from Sami *et al.* (2022), provides a summary of the technical limitations associated with each CV-CPM technique.

Table 3. Summary of technical limitations.

Techniques	***challenges***	***References***
UAVs (Unmanned Aerial Vehicles)	▪ It needs proper operation, ▪ Requires accurate path planning ▪ Requires obstruction avoidance planning ▪ Rotational and sudden angular movements cause blur.	(Hamledari *et al.,* 2021; Braun *et al.*, 2020)
Handheld devices	▪ Views, angles, and coverage depends on human accessibility at the worksite ▪ Required many photographs taken manually ▪ Visual data must go through every nook and cranny of the construction feature under observation	(Hui *et al.*, 2015; Stilla *et al.*, 2015; Shang and Shen, 2017)
Fixed devices	▪ Restricted to a specific view ▪ Minimal maintenance requires significant effort, i.e., crane-mounted cameras ▪ Partial coverage of construction site ▪ Demands many cameras for efficient data collection	(Kim *et al.*, 2013; Masood *et al.*, 2020)
Surveillance cameras	▪ Entails considerable memory requirements ▪ Changing weather conditions can affect the quality of data ▪ Not appropriate for minor features that require a closer view.	(Wang *et al.*, 2020; Fini *et al.*, 2022)
Structure from Motion (SfM)	▪ It takes more time to process larger vision datasets ▪ Les precise compared to other techniques.	(Han and Golparvar-Fard, 2017; Braun *et al.*, 2020)
Convolutional Neural Network (CNN)	▪ The training process requires a considerable time ▪ Higher computing power is needed than ordinary PCs ▪ It will not encode the position and orientation of construction features	(Álvares and Costa, 2018; Braun *et al.*, 2020; Braun and Borrmann, 2019)
Support Vector Machines (SVM)	▪ Not good for larger vision datasets ▪ Do not perform fairly when the dataset gets more noise	(Dimitrov and Golparvar-Fard, 2014; Kropp *et al.*, 2014)
Simultaneous Localisation and Mapping (SLAM)	▪ Produces greater computational complexity in case larger dataset ▪ Image processing requires considerable time and memory	(Shang and Shen, 2017; Kim *et al.*, 2018)

3. Research Methodology

This section provides the details of the research strategy adopted to meet this objective, together with more information on how data was collected and analysed. In addition, the limitations of this work, and potential hurdles identified and addressed.

3.1 Research Design

Research is an activity aiming to contribute more knowledge to the existing body of knowledge (Fellows and Liu, 2008). Collins *et al.* (2014) stated that building new knowledge and exploring the existence of realities require a specific method of inquiry. A research design provides guidelines on which philosophy, approach, and methodology must be taken to fulfil the scientific requirement of good research (Mardiana, 2020). The followings are the key steps in the Saunders research onion approach, including research philosophy, methods, strategies, choices, time horizons, and techniques and procedures.

3.1.1 Research Philosophy

This refers to philosophical assumptions and assists in guiding the study to develop knowledge in a particular field (Saunders *et al.*, 2019). Failure to adhere to philosophical concerns can negatively affect the research quality (Easterby-Smith *et al.*, 2021). There are three philosophies or hypotheses: axiology, ontology, and epistemology. Ontology describes the nature of reality (Saunders *et al.*, 2019). It embodies understanding “what is” (Gray, 2014). Three perspectives guide it: constructivism, objectivism, and pragmatism (Saunders *et al.*, 2009). Epistemology, on the other hand, describes what constitutes adequate knowledge and how it can be acquired (Bhattacherjee, 2012). Two approaches come under epistemology: positivism and interpretivism (Saunders *et al.*, 2019). The researcher requires to reflect on the research assumptions of the five research philosophies. Saunders *et al.* (2015) categorised research philosophies as positivism, critical realism, interpretivism, postmodernism, and pragmatism. The positivist paradigm is adopted in this study as it allows the researcher to use existing theories to formulate hypotheses (Saunders *et al.*, 2015). This philosophy promises unambiguous and accurate knowledge; Positivists promise a scientific method, statistical analysis of the collected quantifiable data, unbiased approach, and generalisable findings (Crotty 1998; Gill *et al.*, 2010). This approach is suitable for a survey type of research strategy.

3.1.2 Research Approach

There are three techniques deduction, induction, and abduction; Inductive and deductive are the two main ones (Saunders *et al.*, 2015; Umar and Egbu, 2018). The deductive approach starts from general to specific; the researcher first examines the existing theories, which leads to a hypothesis then tested using the data collected; In the inductive method, the studies move from specific to general; It is usually applicable in an area characterised by inadequate research, which necessitates theory development (Biggam, 2021). However, according to Ketokivi and Mantere (2010), abductive reasoning urges collecting data to examine a phenomenon, present patterns, and identify themes to develop a new or altered theory. Therefore, this research will take the deductive reasoning approach. Fig.3. The diagram illustrates the difference between deductive and inductive processes.

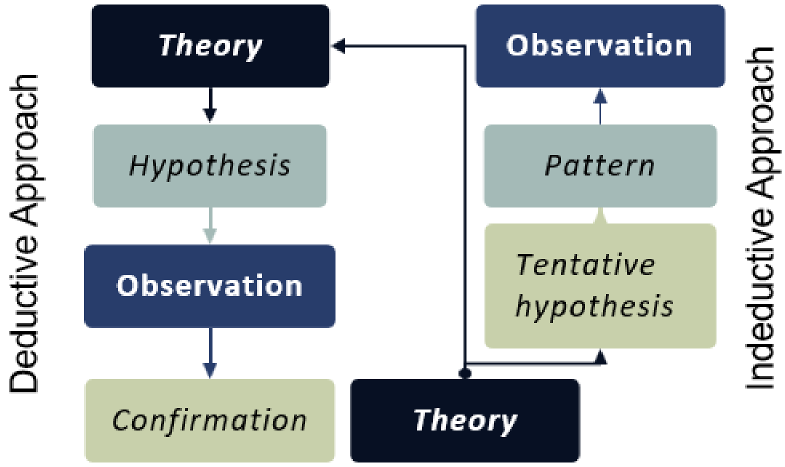


Fig. 13. Deductive vs Inductive Approaches (Source: Balderacchi *et al.*, 2013)

3.1.3 Methodological Choice

As Saunders *et al.* (2019) stated, six methodological choices are defined by the nature of the data collected and the analysis methods. The quantitative method applies numbers and mathematical operations, whilst the qualitative suggests the collection of extensive descriptive data (Umar, 2020; Pandey and Pandey, 2021). The mono method is utilised when a researcher focuses on quantitative/qualitative data gathering; mixed methods (quantitative and qualitative) are employed within the same research to achieve different aims and offset the constraints of using a single method (Saunders *et al.*, 2019). This study falls under the mono-method quantitative choice. Also, AlizadehSalehi and Yitmen (2019) used quantitative methods for automated construction progress monitoring. Table4 illustrates key differences in Quantitative and Qualitative research methods.

Table 4. Methods comparison adopted from Umar (2020) and Pandey and Pandey (2021).

	Quantitative	Qualitative
Underpinning philosophy	Rationalism	Empiricism
Approach to enquiry	Structured/rigid/predetermined/methodology	Unstructured/flexible/open methodology
Main purpose of investigation	To quantify extent of variation ina phenomenon, situations,issue, etc	To describe variation in a phenomenon, situation, issue, etc.
Measurement of variables	Emphasis on some form of either measurement or classification of variables variables	Emphasis on description variables
Focus of enquiry	Narrows focus in terms of the extent of enquiry. but assembles required info from a greater number of respondents	Covers multiple issues but assembles required information from a greater number of fewer respondents
Dominant research value	Reliability and objectivity (value-free)	Authenticity but does not claim to be value-free
Dominant research topic	Explains prevalence, incidence, extent, nature of issues, opinions and attitude; discovers regularities and formulates theories.	Explores experiences, meanings, perceptions and feelings
Analysis of data	Subjects variables to frequency distributions, cross-tabulations or other statistical procedures	Subjects responses, narratives or observational data to identification of themes and describes these
Communication of findings	Organisations are more analytical, drawing inferences and conclusions and testing the magnitude and strength of a relationship.	Organisation is more descriptive and narrative

3.1.4 Research Strategy

This research focuses on "Survey", which is associated with the deductive approach. According to Saunders *et al.* (2019), the method responds to how much, how many, what, who, and where questions for descriptive and exploratory research; survey strategies using questionnaires are common as they allow the collection of standardised data from lots of respondents economically, enabling easy comparison; the survey lets researchers scrutinise data quantitatively employing descriptive and inferential statistics. Therefore, a questionnaire will be employed here to investigate the phenomena (CV-CPM adoption) further and identify the gaps in the practice. The sample for the first data collection stage will be individuals /industry practitioners in the UK. Consequently, the research strategy is descriptive surveys. Cross-sectional and longitudinal are the major timeframes (Wimalaratne and Kulatunga, 2022). This research involves a particular phenomenon at a specific time. Therefore, the research time horizon is identified as the cross-sectional method. Key decisions at this stage include target population, sample size, sampling method, data collection method (questionnaires in this case), data analysis techniques, ethical issues, and research methodology limitations (Saunders *et al.*, 2019). Fig. 4. illustrates a conceptual research methodology framework derived for this study.

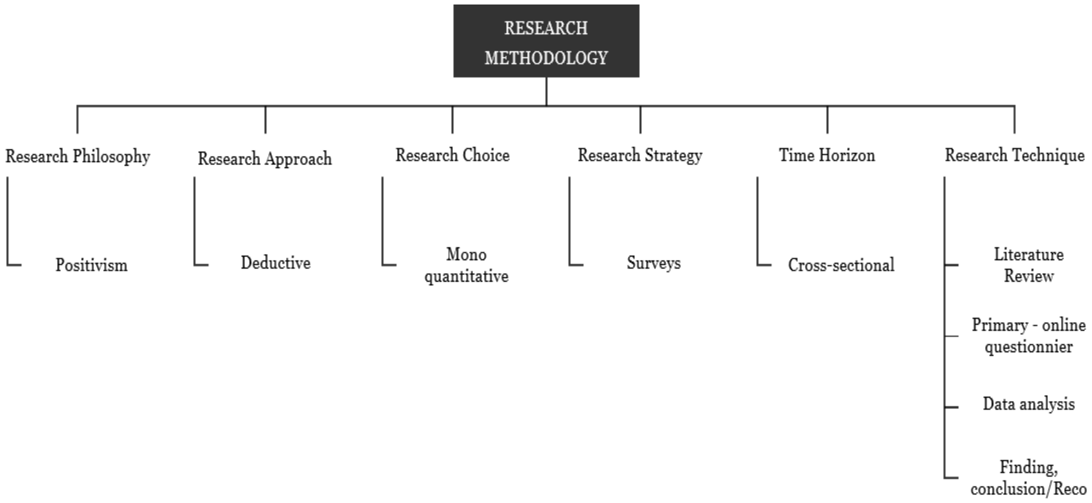


Fig. 4. Conceptual research of this study.

A comprehensive review of related studies and approximately all included items were used from previously reviewed empirical studies to establish a theoretical basis and obtain more in-depth knowledge about CV-CPM and the incentives and barriers to its adoption. Then data collection and analysis were carried out through an online questionnaire with experienced experts practising in the construction industry in the UK. The survey was designed based on Likert scale questions, Multiple choice & some open-ended questions in six sections. The questionnaire was distributed to 81 construction professionals from small, medium-sized, and large-sized. Fifty-three responded with a total response rate of 53%. The results are presented and structured based on the 3 study objectives. Descriptive statistics findings are presented using Qualtrics XM and SPSS statistical analysis software.

3.2. Ethical Considerations

Creswell (2014) states that ethical considerations are essential and must be addressed when conducting a survey. Any phases of this study were carried out carefully not to harm, embrace or force anybody who is participating in this study. To this end, a standard consent form was considered during the online questionnaire to obtain participants' consent. The researcher assured that any data obtained from participants would not disclose or expose the participants' identities. The survey forbade inquiry for sensitive information or persuasive participation with unidentified data gathering and representation. Above all, the data collection, analysis, and disposal processes comply with the University of the West of England (UWE), Bristol ethical policies. This research was considered a low-risk study.

3.3. Validity and Reliability

This study utilises Pearson correlations, which implies the hypothesis of the continuous measurement nature of both latent and observed variables, apart from multivariate normality (DiStefano, 2002). Also, reliability will be established using the "Cronbach alpha" method, the most used measure of internal consistency reliability (Litwin, 2012; Pallant, 2020). Therefore, in this study Statistical Package for Social Sciences (SPSS) will be used alongside Qualtrics XM to test the reliability and validity of the data and questionnaire. As discussed above, this research entails a particular phenomenon in a specific time; therefore, the validity of this study is strictly related to a limitation in time. The significance of this study can be influenced by the validity and reliability of the acquired data.

4. Results and Analysis:

4.1 Response rate, validity and reliability:

The questionnaire was distributed to 100 construction professionals across the UK, and 81 people responded to the survey. However, this study uses only 53 of them for analysis, with a total response rate of 53%, as 28 of the responses are unused due to missing information/uncompleted surveys.

The Cronbach's alpha value was calculated as 0.855 utilising SPSS, leading to the conclusion that the questionnaire is reliable. As Bolarinwa (2015) stated, values of Cronbach's alpha greater than 0.7 represent acceptable reliability.

To assess the validity of the survey, the Pearson correlation (Bivariate correlation) was analysed, and the result demonstrated an acceptable degree of correlation consistency between the study and the obtained value, highlighting the validity of the questionnaire. As shown in Table 5 a good relationship between variables with precise measurements close to +1 and -1 was also observed. Note that the relation between the correlation coefficient and the t-ratio (Weathington *et al.*, 2012):

$$r_c = \frac{t_c}{\sqrt{(n-2)+t_c^2}}$$

Table 5. Pearson correlation assessment of the survey using SPSS IBM.

SUMMARY OF PEARSON CORRELATIONS COMPARISON
(Obtained correlation coefficient against the critical values)

Questions	*Sig. (2-tailed)*	*N*	*P-correlation (obtained)*	*D.F.*	*P-Critical Values (0.05)*
QU 4	0.605	51	-0.074	49	0.273
QU 5	0.035	53	.290*	51	0.250
QU 6	0.246	53	0.162	51	0.250
QU 7	0.740	53	-0.047	51	0.250
QU 8	0.887	53	-0.020	51	0.250
QU 9	0.587	53	0.076	51	0.250
QU 10	0.600	53	0.074	51	0.250
QU 11	0.908	22	0.026	20	0.423
QU 12	0.165	49	-0.201	47	0.231
QU 13	0.134	53	0.209	51	0.250
QU 14	0.001	53	0.446**	51	0.250
QU 15	0.004	53	0.388**	51	0.250
QU 16	0.000	53	0.534**	51	0.250
QU 17	0.000	53	0.541**	51	0.250
QU 18	0.000	53	0.544**	51	0.250
QU 19	0.021	52	0.321*	50	0.273

*. Correlation is significant at the 0.05 level (2-ailed).
**. Correlation is significant at the 0.01 level (2-tailed).
Close to -1: perfectly negative linear relationship | +1: perfectly positive linear relationship (Weathington *et al.*, 2012)
d.f.= the number of pairs of scores minus 2.
(Weathington *et al.*, 2012)
Table of critical values for Pearson's r (source: Weathington *et al.*, 2012)

4.2 Survey result

4.2.1 Respondents' Demographics

According to the survey, the respondents work in companies of different sizes in the UK. This includes 21 from small (1-49), 11 from medium-sized (50-500), and 19 from large (500+). In addition, participants were asked which areas of construction their company has been involved in. Fig. 5. presents the companies' main business activity and the percentage.

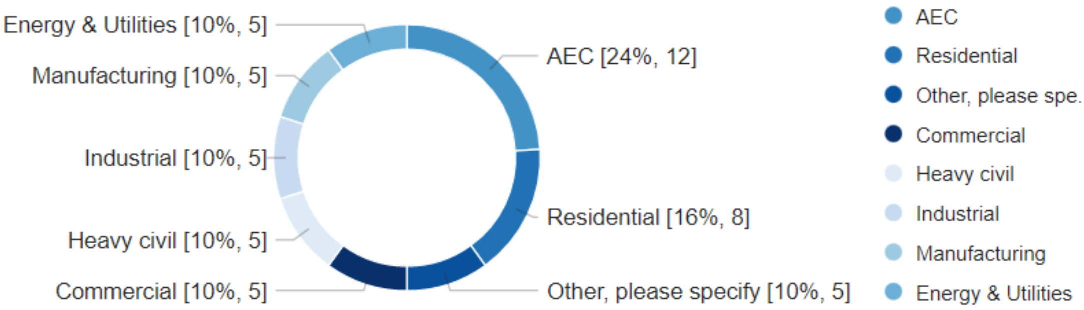


Fig. 5. Companies' main business activity

The respondent qualities were also analysed to interpret the results better. Fig.14. presents the percentages of respondents by their positions. In addition, according to Fig. 6. & 7., most respondents are project managers working at small and large-sized companies.

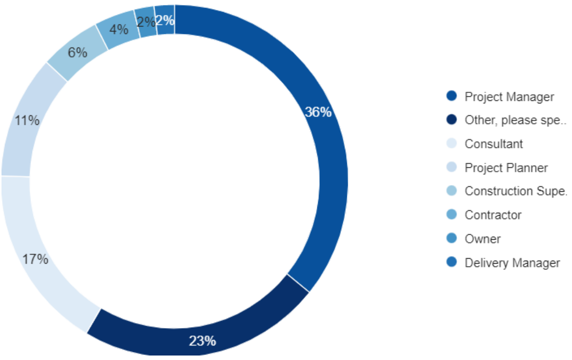


Fig. 6. Participants' designations

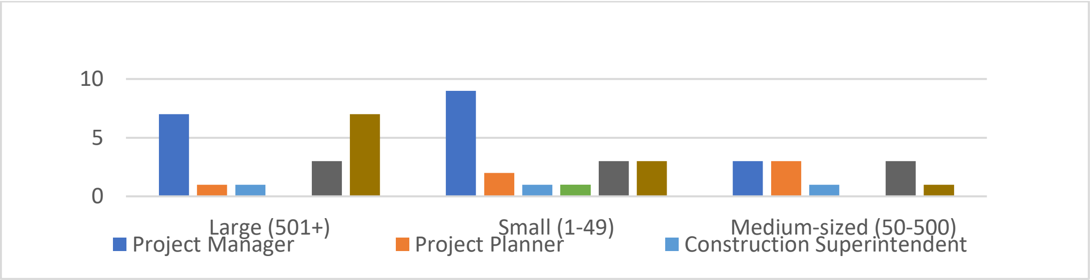


Fig. 7. The proportion of participants' roles.

The remaining ratio represents other (quantity surveyors & civil engineers), consultants, planners, construction superintendents, contractors, owners, and delivery managers with the approximate proportion of 23%, 17%, 11%, 6%, 4%, and the remaining two roles with 2% evenly which verifies a wide range of participants contributed in this survey to empower validity of the responses.

As for education, 93% of the participants hold a master's and bachelor's degree, 53% and 40%, respectively. The remaining hold PhD and high school diplomas or lower with an identical proportion of 4%. Regarding work experience, 26% of participants had 10+ years of experience, 23% (5-10), 21 % (1-3), and 15% from 3-5 years of experience. Likewise, those who had only one year of experience were 15%. Consequently, nearly 48% of respondents had 5+ years of experience, which is a notable amount of work experience in the industry. Fig.8. presents the data concerning the education and work experience of respondents.

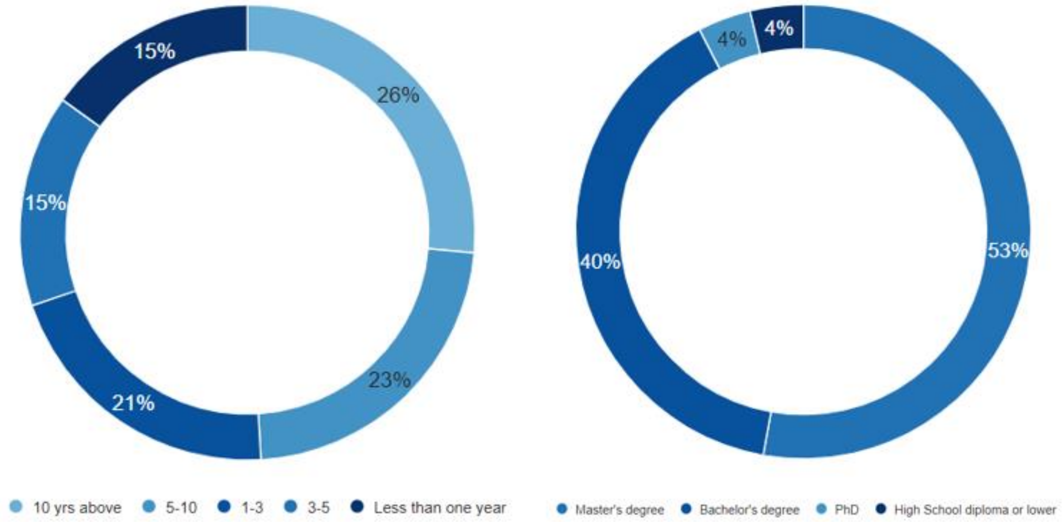


Fig. 8. Education level and work experience of the participants

In addition to demographic information, participants were surveyed about their awareness of CV technology and its usage. Respondents were asked if they or their company currently use Computer Vision (CV) or other technologies in their construction progress monitoring (CPM) practices; of those who responded, 66% stated they or the company, irrespective the size, does not use it, and 34% is using it.

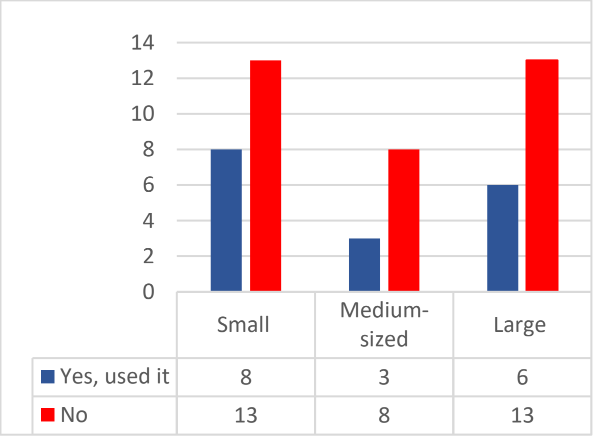


Fig. 9. CV-CPM uses among UK companies.

Fig. 9. reflects detailed use values among UK construction, including small, medium, and large-sized companies. As the pie charts below show, about 23 (43%) of the respondents were unaware of CV, and only 15(28%) responded that they are aware of it. The remaining 16 (29.6%) appear to be familiar with the CV-CPM but have not used it. Of those who responded to if they had ever used CV or been involved in smart monitoring, 20% used it in CPM, 18% in safety, and 2% in quality monitoring. The

responses demonstrate that nearly 60 % of the participants have never employed visual assessment technology. (See fig.10.)

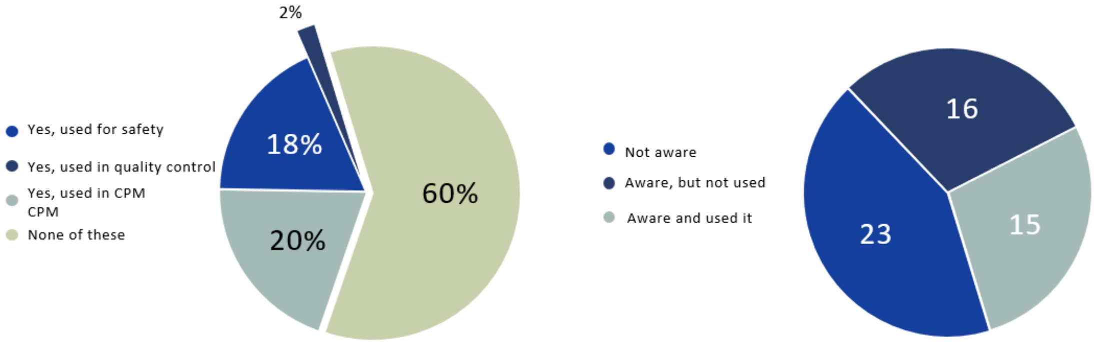


Fig. 2. Level of awareness and CV usage.

The responses show that 32.7% of large companies currently use CV-CPM technology. At the same time, this is 39.3% and 28.3%, respectively, for small and medium-sized. However, the figure represents that almost 2/3 of all-sized companies have not deployed it (small 60.7%, medium 71.7%, and large 67.3%), which is a significant gap, as shown in fig.18. The participants were further asked when they plan to use it If they do not use CV on your construction site. In reply, 43% indicated within 1-5 years, and 27% pointed within 5-10 years. Moreover, 18% of those who responded were unsure, while the remaining 10% believed it would be over ten years. Only 2% indicated they “Never” would use a CV on their construction site.

Eventually, participants were asked to rate their CPM and CV-CPM competence levels. As shown in fig.11., the responses exhibit that most participants have a fair to satisfactory knowledge of CPM. As for CV-CPM, while the majority have nil to fair proficiency level, the level of expertise of CV-CPM is still quite low among construction professionals.

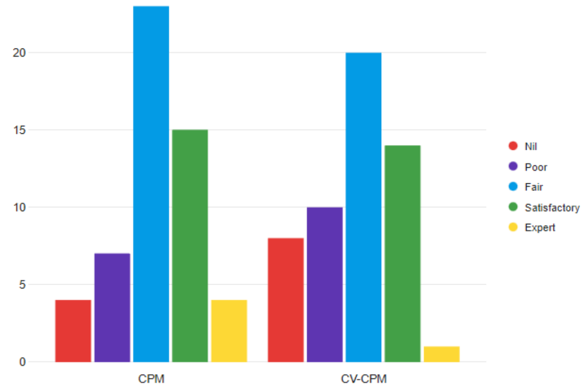


Fig. 3. Competence level in CPM/CV-CPM

4.2.2 Relative advantages over traditional CPM

The results display that most respondents agree with the relative benefits of CV-CPM over the conventional approach. The CPM function refers to the required output of the site performance, and the process relates to controlling those activities carried out during planning and scheduling. Table 6 presents the ranking based on respondents' standpoints: Schedule optimisation and real-time data collection are mostly favoured. Controlling project performance, task completion, and transparency/accuracy with the same value stands top second picks. Identifying time discrepancies, active decision-making, and change detection was picked as the third top-ranked by the respondents. Conversely, functions such as quantifying project progress and dispute avoidance are both ranked the lowest, though still more preferred than the traditional method.

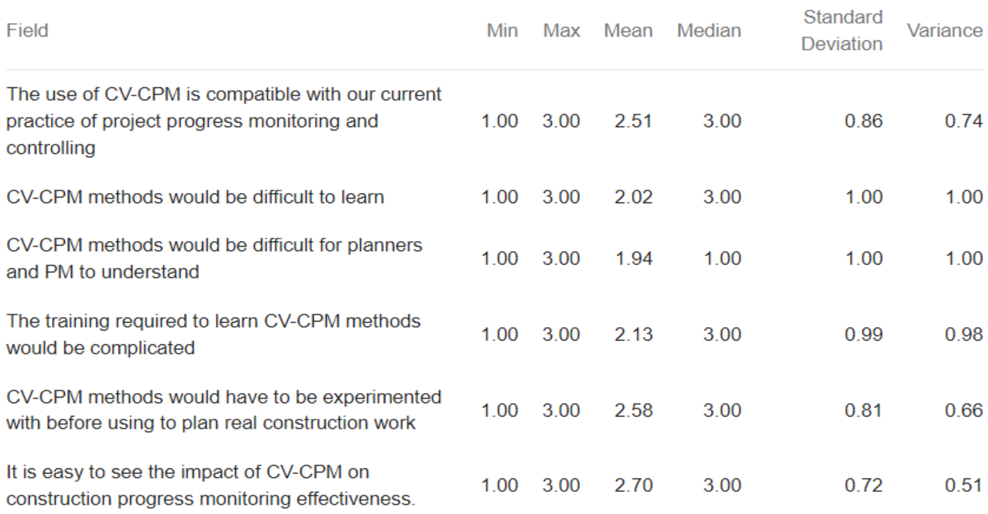
Table 6. Relative advantages of CV-CPM over traditional CPM

Field	Min	Max	Mean	Median	Standard Deviation	Variance
Time schedule optimisation	2.00	4.00	3.74	4.00	0.48	0.23
Real-time data collection	2.00	4.00	3.72	4.00	0.49	0.24
Controlling project performance	2.00	4.00	3.70	4.00	0.50	0.25
Task Completion	2.00	4.00	3.70	4.00	0.50	0.25
Transparency and accuracy	2.00	4.00	3.70	4.00	0.50	0.25
Identifying time discrepancies	2.00	4.00	3.68	4.00	0.58	0.33
Active decision making	2.00	4.00	3.68	4.00	0.58	0.33
Change detection	2.00	4.00	3.66	4.00	0.55	0.30
Track equipment and material which affects time schedule	2.00	4.00	3.62	4.00	0.59	0.35
Lawsuit/dispute avoidance (Time wise)	2.00	4.00	3.51	4.00	0.60	0.36
Quantifying project progress	2.00	4.00	3.51	4.00	0.63	0.40

4.2.3 The perceived characteristics

The first inquiry relates to compatibility, followed by three questions to calculate the complexity and the last two to review the trialability and observability characteristics. Among those who responded, the outcomes reveal that the CV-CPM is somewhat compatible, and it is easy to see the positive impacts in some ways. For complexity, CV-CPM is seen to be somehow complicated for all-sized companies, yet participants highlighted that it would be more complex for project planners to learn. The trialability characteristic of the CV-CPM innovation findings points out positive feedback from most participants. That means there is a chance to try a pilot project before full implementation. Notwithstanding, as shown in Table 7 and fig. 12. participants have given more frequency of agreement to each of these statements.

Table 7. CV-CPM Perceived characteristics.



Field	Min	Max	Mean	Median	Standard Deviation	Variance
The use of CV-CPM is compatible with our current practice of project progress monitoring and controlling	1.00	3.00	2.51	3.00	0.86	0.74
CV-CPM methods would be difficult to learn	1.00	3.00	2.02	3.00	1.00	1.00
CV-CPM methods would be difficult for planners and PM to understand	1.00	3.00	1.94	1.00	1.00	1.00
The training required to learn CV-CPM methods would be complicated	1.00	3.00	2.13	3.00	0.99	0.98
CV-CPM methods would have to be experimented with before using to plan real construction work	1.00	3.00	2.58	3.00	0.81	0.66
It is easy to see the impact of CV-CPM on construction progress monitoring effectiveness.	1.00	3.00	2.70	3.00	0.72	0.51

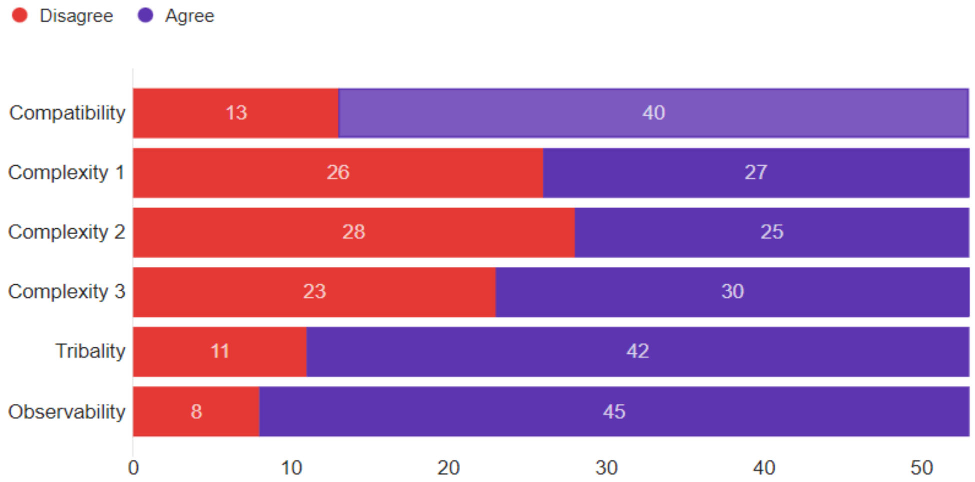


Fig. 12. The identified characteristics of CV-CPM technology innovation.

4.2.4 CV-CPM use

The responses revealed functions such as "reporting project progress, validating and schedule analysis, and equipment tracking as the least used functions. Table 8 shows the frequency of usage in detail.

Table 8. The extent of CV-CPM functions used. (Never – Sometimes – Always)

Field	Min	Max	Mean	Median	Standard Deviation	Variance
Change Management (Time)	1.00	5.00	2.96	2.00	1.79	3.19
Data collection	1.00	5.00	2.92	2.00	1.79	3.20
On-site material tracking (Inventory)	1.00	5.00	2.74	2.00	1.74	3.02
Progress comparison (actual Vs planned)	1.00	5.00	2.73	2.00	1.70	2.89
Monitoring and controling	1.00	5.00	2.66	2.00	1.66	2.75
Machinery and equipment tracking	1.00	5.00	2.64	2.00	1.67	2.80
Validating and analysis of the schedule	1.00	5.00	2.62	2.00	1.68	2.84
Reporting project progress	1.00	5.00	2.36	2.00	1.49	2.23

4.2.5 Incentives for CV-CPM

Table 9 show that participants believe technological development will improve the decision-making process and strengthen competitive advantages (ranks 1,2,3). Therefore, CV-CPM would be strategically important to implement in UK construction sites, and the variable ranked 4 with a mean of 5.06. The responses, however, reveal that the main constraints are not easy adoption of CV-CPM and insufficient internal expertise, with the least mean values, ranked 8 and 7, respectively.

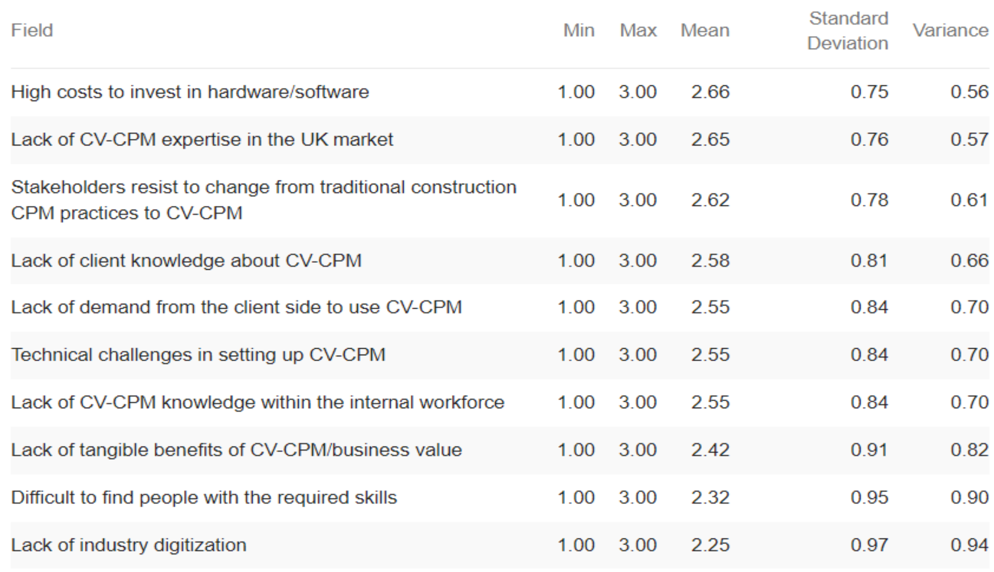
Table 9. Incentives to adopt CV-CPM in UK construction sites.

Field	Min	Max	Mean	Standard Deviation
By adopting CV-CPM, the company can follow the technological development	1.00	6.00	5.43	1.58
CV-CPM improves the decision-making process	1.00	6.00	5.34	1.69
CV-CPM will give us competitive advantages	1.00	6.00	5.23	1.80
It is believed that CV-CPM innovation would be of strategic importance for the company	1.00	6.00	5.06	1.96
Getting good support from external actors/consultants to use CV-CPM in our projects.	1.00	6.00	4.77	2.15
Perceiving a strong internal demand for CV-CPM	1.00	6.00	4.49	2.30
The company enough internal expertise capacity to implement CV-CPM	1.00	6.00	4.46	2.31
CV-CPM is straightforward/easy to adopt	1.00	6.00	4.02	2.45

4.2.6 Barriers to CV-CPM adoption

As shown in table 10, the top three barriers are the high cost of technology (Soft/hardware), lack of expertise, and resistance to changing the CPM method. In contrast, lack of digitisation ranked as the least barrier to adopting CV-CPM with a means of 2.25. Next, the lack of knowledge, client demand, and technical challenges are ranked as 4th, fifth, and sixth (the second top) barriers to implementing CV-CPM in UK construction sites. Nonetheless, the third top barrier group observed is connected to the internal organisation: lack of internal knowledge and lack of tangible benefits.

Table 10. Impediments to adopting CV-CPM in UK construction sites.



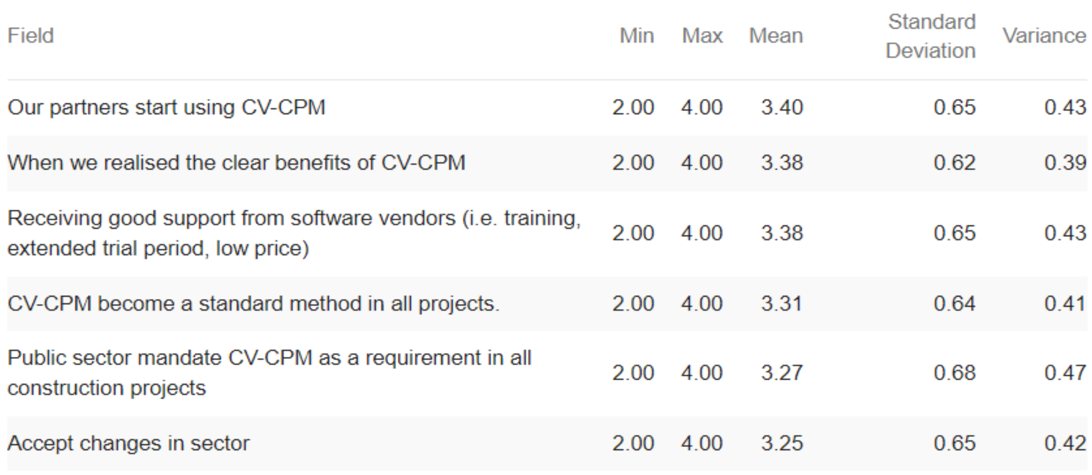
Field	Min	Max	Mean	Standard Deviation	Variance
High costs to invest in hardware/software	1.00	3.00	2.66	0.75	0.56
Lack of CV-CPM expertise in the UK market	1.00	3.00	2.65	0.76	0.57
Stakeholders resist to change from traditional construction CPM practices to CV-CPM	1.00	3.00	2.62	0.78	0.61
Lack of client knowledge about CV-CPM	1.00	3.00	2.58	0.81	0.66
Lack of demand from the client side to use CV-CPM	1.00	3.00	2.55	0.84	0.70
Technical challenges in setting up CV-CPM	1.00	3.00	2.55	0.84	0.70
Lack of CV-CPM knowledge within the internal workforce	1.00	3.00	2.55	0.84	0.70
Lack of tangible benefits of CV-CPM/business value	1.00	3.00	2.42	0.91	0.82
Difficult to find people with the required skills	1.00	3.00	2.32	0.95	0.90
Lack of industry digitization	1.00	3.00	2.25	0.97	0.94

Objective 3: To investigate solutions and drivers influencing CV- CPM implementation within UK construction Sites.

4.2.7 Solution/ Driving forces

With a very close mean value, "our partner started using it" and "when the company realised the clear benefits of CV-CPM" were selected respectively as the leading solution. Additionally, "receiving adequate support from software vendor (training, trial period, low price)"was ranked number 3. It should be noted that "accepting changes in the sector ranked the least important driver to the adoption of CV-CPM according to responses. (See table 11)

Table 11. Solutions and driving forces to seize barriers and adopt CV-CPM.



Field	Min	Max	Mean	Standard Deviation	Variance
Our partners start using CV-CPM	2.00	4.00	3.40	0.65	0.43
When we realised the clear benefits of CV-CPM	2.00	4.00	3.38	0.62	0.39
Receiving good support from software vendors (i.e. training, extended trial period, low price)	2.00	4.00	3.38	0.65	0.43
CV-CPM become a standard method in all projects.	2.00	4.00	3.31	0.64	0.41
Public sector mandate CV-CPM as a requirement in all construction projects	2.00	4.00	3.27	0.68	0.47
Accept changes in sector	2.00	4.00	3.25	0.65	0.42

5 Discussion and Conclusion

5.1 Discussion

The findings show that almost half of the participants in the UK are aware of CV technology; however, around two-thirds of them have never used CV in their CPM practice (Fig. 11). This illustrates inadequate knowledge and competency levels in CV-CPM. The low proficiency level can be attributed to a lack of competencies and skills (Sami *et al.*, 2022). Literature also reveals the industry's struggle with low competency among construction workers and professionals (Oesterreich and Teuteberg, 2016). Despite this, most participants agree that CV-CPM offers advantages over traditional CPM, particularly in optimizing schedules and real-time data collection capabilities. Active on-demand data collection provides fast and responsive assessments, aiding in schedule optimization and resource planning. CV-CPM's ability to automatically detect and determine significant changes on-site is seen as an advantage in change management. Automatic data collection is also valued for its ability to remove manual data collection, reducing human errors and improving data quality. Overall, except for a few functions, the level of use remains relatively inadequate, indicating that companies in the UK have not fully realized the potential of CV-CPM (Vilde, 2021). The respondents report that high cost, lack of CV-CPM expertise, and resistance to change are the most significant concerns for adopting CV-CPM, with mean scores of 2.66, 2.65, and 2.62, respectively. Modern technology transformation is perceived as a risk, and the high cost of implementation is seen as a burden due to unclear benefits in terms of cost savings and investment requirements. This perception leads to the belief that innovative technologies are costly to implement (Zhou *et al.*, 2015; Oesterreich and Teuteberg, 2016; Dallasega *et al.*, 2018; Demirkesen and Tezel, 2021). The lack of expertise is also identified as a significant challenge for CV-CPM adoption. Given the conservative nature of the construction sector, resistance to change is expected and is considered an important barrier.

In addition to the main concerns, respondents also rank "lack of client knowledge," "client demand," and "CV-CPM knowledge within the internal workforce" as other barriers to CV-CPM adoption. These issues of lacking skills and knowledge are prevalent within both clients and the internal workforce in the construction industry, making it challenging to implement CV for CPM (Morgane *et al.*, 2022). Client demand plays a significant role as construction companies are more motivated by client demands (Kassem *et al.*, 2012). Studies have reported that unclear benefits directly affect technology adoption in the industry. The findings indicate that technological development, improvement in decision-making, and gaining competitive advantages are significant incentives for companies. Technological development is crucial for enhancing competitive advantages (Nam and Tatum, 1988). It is theoretically justified and empirically confirmed that competition is a vital motivator for innovation (Mitropoulos and Tatum, 2000; Sayfullina, 2010). Companies are driven to maintain resilience and pursue further improvements to achieve greater financial benefits.

Lastly, the survey results reveal that "partners/peers" play the most active role in driving the adoption of CV-CPM, followed by realizing clear benefits and receiving support from the vendor. This indicates that the UK construction industry is willing to accept CV-CPM only when they see tangible results and benefits. It is believed that the influence of mimetic pressures on CV-CPM adoption can be partially mediated by client/owner/government sponsorship. As mentioned earlier, companies embrace technology when they have clarity on the technological and financial benefits.

This study demonstrates that respondents perceive CV-CPM as having a greater relative advantage, good compatibility with current practices, good trialability, and observability. However, the complex nature of the process and the difficulty in learning and understanding have hindered the diffusion of CV-CPM innovation. The findings highlight "high cost and unclear benefits" as the top barriers. Additionally, considering the institutional concept, the solution of "our partners start using it" indicates that companies are influenced primarily by mimetic pressure. In a broader sense, if "our partners/firms are not using CV-CPM," it can be considered a barrier, while their adoption can be seen as a solution. This reveals that UK construction companies are uncertain about embracing CV-CPM due to hesitation about the benefits and gains.

5.2 Conclusion

Construction is recognized as a major influencer in the UK economy, but it faces numerous challenges, particularly in managing and controlling projects due to reliance on manual data collection. CV application has the potential to bring many benefits and standardize the CPM process. CV-CPM can eliminate redundancies and errors, making the process more reliable. Therefore, this research aimed to investigate the usage and advantages of CV-CPM over traditional approaches, the challenges of CV-CPM implementation, and the incentives and drivers influencing CV-CPM implementation in UK construction sites. Through a comprehensive literature review, followed by a quantitative survey, the study sought to achieve these objectives.

The analysis reveals that while awareness of CV-CPM among UK construction professionals is fair, there is a lack of knowledge and skills. The results indicate that CV-CPM is considered superior to the traditional approach, but its usage level remains low regardless of company size. This may be due to the relatively new concept of CV-CPM and its limited use for progress measurement in UK construction, with a greater focus on change management and material tracking. The survey also identified the most significant barriers to CV-CPM adoption, including the cost of implementation, lack of expertise, and resistance to change. Incentives for CV-CPM use were also analysed, with technological development, improved decision-making, and competitive advantages identified as significant factors, as technological advancement is crucial for gaining competitive benefits. Solutions to address these barriers were found in the form of mimicking peers (partners starting to use CV-CPM) and clear benefits that companies can observe. In conclusion, the implementation of CV-CPM technology can enhance progress detection operations and data accessibility on UK construction sites. However, successful implementation requires careful consideration of financial impacts and the development of strategies to address unknown benefits and gains. To overcome resistance to change, companies must foster a culture of change and provide training to enhance workforce awareness, preparing the industry for a smooth transition.

The main contribution of this study is providing construction professionals with a comprehensive list of barriers and incentives for CV-CPM adoption. Industry practitioners can benefit from these findings and detailed evaluations to develop successful adoption and transformation strategies, as CV-CPM has the potential to accelerate progress detection and data accessibility. Despite the valuable contributions of this study, there are limitations. The survey sample size was small, representing only a portion of UK construction professionals, and therefore reflecting the thoughts and opinions of a limited population. Future research could expand on this by examining the knowledge level of respondents regarding CV-CPM adoption in UK construction sites. Additionally, other key factors that were not investigated due to time limitations could be explored further. Future case studies focusing on practical implementation could provide a better understanding of the challenges, possibilities, and drivers for CV-CPM in UK construction sites.

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Figure Caption List

Table Caption List