The Implementations of Smart Monitoring on Construction Sites – A Literature Review

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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 computer vision-construction project management (CV-CPM) adoption and the main barriers to and incentives for its adoption within UK construction sites. In this respect, 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 was conducted with a specific focus on the UK construction industry. 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. The main contribution of this study is to provide construction professionals with a comprehensive list of barriers and incentives toward CV-CPM adoption. Industry practitioners might benefit from this research's findings and detailed evaluations to develop successful adoption and transformation strategies as CV-CPM can accelerate the progress detection and data accessibility for outcomes.

Keywords

Computer vision, Project Management, Monitoring, Controlling, Artificial Intelligence, Performance, Productivity, Innovation, Automation

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. 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. since the research is in progress therefore, this paper only utilize the literature review approach as discussed in Umar (2020) to arrive on current finding.

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

According to Acaster et al. (2017), monitoring and control are all about decision-making, and it is the centre of project management; the aim is to carry out the work according to program, resource and cost plans and maintain viability against the business case. Furthermore, monitoring collects, records, and reports information concerning project performance (PMBOKGUIDE, 2021), during the execution and pinpointing lagging areas requiring awareness and action. Inadequate and imprecise monitoring and tracking are two major factors that account for time and cost inefficiencies in projects (Ekanayake et al. 2021; Omar et al., 2018). Systematic monitoring could be complicated as the current method is time-consuming (Golparvar-Fard et al.,2009). This manual data collection causes errors and diminishes the data quality (Kiziltas and Akinci, 2005). Current methods create a bias (Mantel and Meredith, 2009). It also creates a time lag between reported and accomplished progress (Golparvar-Fard et al., 2011). It is visually complicated and does not reflect spatial features of site progress with its associated complexity (Koo and Fischer 2000).

2.3 Role of AI technology in construction management

Artificial intelligence (AI) is the backbone of this change to launch real digital strategies (Pan and Zhang, 2021). AI drives computers to sense and learns inputs like a human for perception, knowledge model, logic, problem-solving, and planning, which can deal with complicated and fuzzy problems intelligently and adaptively (Thomas and Zikopoulos, 2020: p.20). In project management makes the process more technically automatable and accurate (Pan and Zhang, 2021). The insights acquired from such cutting-edge analytics aid in better understanding the project's construction, standardising implicit knowledge from project experiences, and rapidly spotting the project matters in a data-driven manner (Hu and Castro-Lacouture, 2019).

2.4 The concept, function, and usage of (CV)

This technology stimulates computers to drive influential data from images, videos and other observable inputs and make recommendations; in effect, Artificial intelligence lets the machine judge and CV authorise them to observe and comprehend (IBM, 2022). With a large amount of visual data it generates, the construction industry can greatly benefit from the automatic extraction and analysis of this useful data (Paneru and Jeelani, 2021). A typical concept of a computer vision-based system is shown in figure 1.

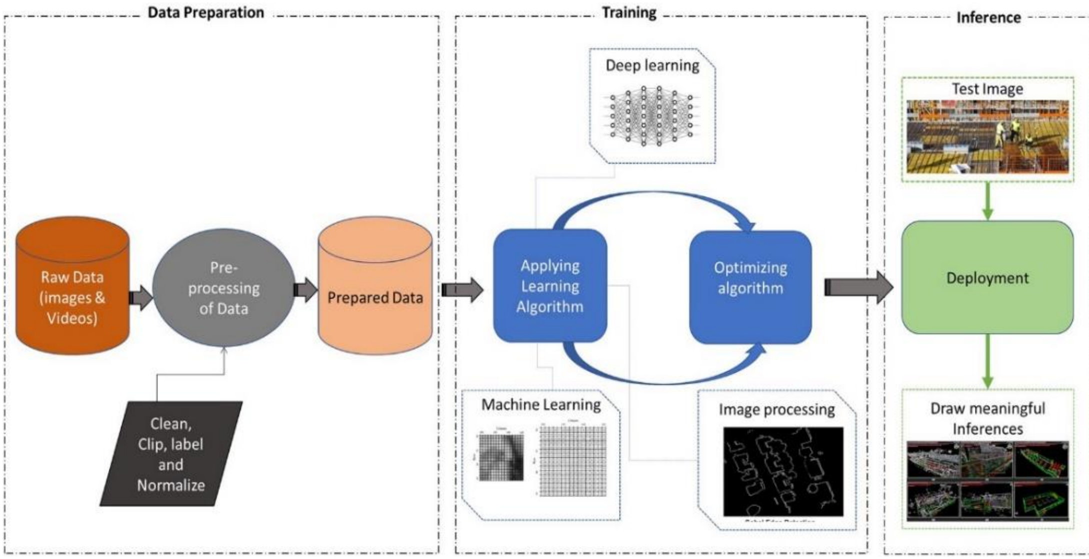

Fig. 1. A typical concept of a computer vision-based system (source: Paneru *et al.* 2021)

2.5 Integration of CV with CPM

CV has enabled the development of automating various tasks involved in progress monitoring (Paneru and Jeelani, 2021). It can trace multiple entities within a camera view and overcome current challenges (Park et al., 2011). Extracting comprehensive information from the images can help automate diverse construction-related activities (Paneru and Jeelani, 2021). CV enables computers to derive numeric information from videos, depth images and 3D point clouds, process the data, and act (Reja et al., 2022). According to Kopsida and Brilakis (2020), different technologies can generate inputs through image frames or point clouds. It can be fixed, handheld or robotic systems mounted on UGV or UAV (Adán et al., 2020). The key factors that govern their selection include the level of automation for data capture (Reja et al., 2022). Reja et al. (2022) study suggested an integrated CV-CPM framework with various concepts and technologies to automate CPM.

2.6 Benefits/Drivers

CV-CPM has the potential to create an immense impact by providing real-time, accurate, reliable information to construction managers (Reja et al., 2022). The method offers an inexpensive solution (depending on the technology) to automated monitoring processes (Panahi et al., 2022). Few scholars, including Brilakis et al. (2011); Ekanayake et al. (2021), found that using CV optimises and increases the efficiency of construction work monitoring and tracking. It also can track the activities of plants and machinery to determine their efficiencies and impact on construction progress (Morgane et al., 2022). Consistently on-demand snapshots deliver a quick assessment (Ibrahim et al., 2009) and help to optimise schedule and resource planning (Paneru and Jeelani, 2021). Prompt assessment of CV-CPM offers accuracy, reliability, and transparency (Ibrahim et al., 2009). CV-CPM authorises project hindrances to be identified earlier for respective countermeasures (Braun and Borrmann, 2019). Also, planners can check project history for delays in root cause analysis and react efficiently (Alizadehsalehi and Yitmen, 2019). CV-CPM can analyse with high effectiveness, quantify site progress, and stop PMs from manually monitoring and investigating progress status and performance, letting them focus on budget and time control (Teizer, 2015). It also helps to forecast progress and simulate and evaluates control measures to bring the project back on track (Reja et al., 2022). It will aid decrease the threat of errors and re-work and prevent time and cost deviations (Kopsida et al., 2015). Also, promoting methods to implement CV by integrating it with BIM will allow it to be further automated and reduce the extent of human intervention (Morgane et al., 2022). It would be the most appropriate input to capture geometrical attributes directly and fast (Reja et al., 2022). The visual assessment of CV-CPM can automatically detect and determine significant changes on-site by comparing digital images to the geometric and material properties of components and activities using ML algorithms (Ibrahim et al., 2009). This significantly helps PMs and project planners to control changes better.

Zhang et al. (2009) stated that CV-CPM could provide visual and quantity details, which could be utilised as evidence for potential contractual claims. (See table 1) His study has also demonstrated CV-CPM's schedule and cost control ability by constantly providing early alerts on possible delays.

Table 1. CV-CPM Added value (Source: Zhang *et al.*, 2009)

Variable	1 (very low)	2 (low)	3 (average)	4 (high)	5 (very high)	Mean	Standard Deviation
Work Package Planning and Formulation	0.0%	12.5%	12.5%	62.5%	12.5%	3.75	0.886
Cost and Schedule Control	0.0%	12.5%	12.5%	50.0%	25.0%	3.88	0.991
Calculation of Interim Valuation/Payment	0.0%	0.0%	37.5%	50.0%	12.5%	3.75	0.707
Cashflow Analysis	0.0%	0.0%	50.0%	25.5%	25.0%	3.75	0.886

CV-CPM can update schedules and generate reports/notifications, including progress quantification (Reja et al., 2022). These advantages of CV-CPM can positively influence firms to be innovative. Innovation drivers and motivation creates technological advancement (Suprun and Stewart, 2015). Several researchers claim that technological advancement is necessary if companies want to improve their competitive advantage. Competitiveness is one of the aspects impacting the maturity of the construction company for CV-CPM innovation (Johansson and Opseth, 2021). The desire of institutions to know competitive advantage is a significant driver of innovation diffusion (Sayfullina, 2010). The advantages of CV-CPM innovation include improved leadership and decision support system, save time and improve productivity, better document quality, process and performance improvement, tracking equipment and material which affects the schedule, change detection, dispute avoidance, and improve transparency and accuracy.

2.7 Challenges to CV-CPM adoption

While CV-CPM has the potential to create an enormous impact by providing real-time, accurate, reliable information to construction managers, specific challenges remain due to the construction industry's dynamic nature and site complexities (Qureshi et al., 2020). Odubiyi et al. (2019) divided the challenge to new technologies into three categories: technology, methodology, and individuals. Sardroud (2015) categorised them into cost-related, process-related, and technology-related matters, as most impediments are people-related; solutions will be discovered by scrutinising the factors that construction stakeholders perceive as hindrances. Arabshahi et al. (2021) barriers can normally be stakeholders' perceptions, such as perception of operating cost, lack of well-trained staff, and technology immaturity. The initial cost of implementation has also been cited frequently as a major obstacle (Alizadehsalehi and Yitmen, 2019). Hidden costs of training, maintenance, and operation are challenging implementation (Goodrum et al., 2011). According to Martinez et al. (2019), the cost of storing all the obtained data is a challenge. Since the construction industry is dynamic and complex, the cost of implementing new technology is a risk for most firms (Demirkesen and Tezel, 2021).

Besides cost-related barriers, challenges related to people are also involved, such as a lack of interest and well-trained staff (Singh et al., 2011; Didehvar et al., 2018). The fragmented nature of the construction sector leads to low awareness of innovative approaches and the adoption of innovative technologies (Shen et al., 2010; Evans and Heimann, 2022). The industry suffers from the low competency of construction workers and professionals (Oesterreich and Teuteberg, 2019). Recent technologies will require competencies, including skills and knowledge; competencies enable people to embrace modern technology, "adapt to its use and continue to iterate how it is used." (CITB, 2018). Hewage et al. (2008) highlighted that lack of expertise makes managers doubt whether the available labour force is confident in using modern technologies in building projects. They added that companies are reluctant to welcome recent technologies with insufficient skills and expertise. Doloi et al. (2012) believe that it becomes troublesome for construction companies to start a transformation process for industry 4.0 when expertise is lacking. According to Morgane et al. (2022), the unavailability of human resources with good proficiency in computational areas in construction would also become a barrier to implementing CV-CPM. The sector is conservative concerning embracing change; but innovative technology requires a shift, which emerges as a substantial challenge for CV-CPM adoption by the industry (Oesterreich and Teuteberg, 2016; Trstenjak and Cosic, 2017; Woodhead et al., 2018). Implementation requires process changes at all levels of the organisation; however, the industry is historically resistant to change (Young et al., 2021). Therefore, due to resistance, the construction industry has been recognised as one of the least digitised sectors (Abioye et al., 2021). Golizadeh et al. (2019) also believe that changes in the management process and complications in the construction site also influence technology adoption.

Unclear benefits and returns cause the unwillingness to welcome change and invest in innovative technologies (Demirkesen and Tezel, 2021). Several studies highlighted that companies are biased against implementing industry 4.0 and AI in construction since they are unclear about its benefits in cost savings and investment requirements; hence, they perceive modern technologies as costly to implement (Zhou et al., 2015; Oesterreich and Teuteberg, 2016; Dallasega et al., 2018). In this context, Luthra and Mangla (2018) further mentioned that most industries are reluctant to adopt smart technologies due to ignorance of the potential benefits. Therefore, it is critical for construction companies not to have a definite plan for the unknown benefits and returns on investment (ROI).

Besides, the SmartMarket report (2012) stated that 55% of companies that do not embrace automation technologies on project sites lack requirements from the client side. This means that the construction players will be more influenced by clients' demands (Kassem et al., 2012; Mitropoulos and Tatum, 2000). For example, NBS (2019) reported that the most common barriers to implementing innovative technologies are "lack of client demand" (65%) and "lack of in-house expertise" (63%). Several studies further describe the lack of clients' demand for technology adoption (Eadie et al., 2013; Vass and Gustavsson, 2017). Various Barriers identified to the adoption of CV-CPM include operation cost, cost of training and employing professionals, maintenance, cost of implementation, uncertain cost-benefit relation, operational difficulties, data management issues, and technology immaturity.

Institutional constraints may prevent the adoption of CV-CPM. The institutional theory defines the resilience and transformation of an institution. In this theory, three divers affect institutions to become isomorphic: coercive, normative, and mimetic (Cao et al., 2014). Two forces drive coercive isomorphism: pressures from other organisations on which it depends and an organisation's pressure to conform to the cultural expectations of the larger society. In a broader sense, forces bring an organisation's structure in line with the demands of powerful alters (Mizruchi and Fein, 1999). When the public sector changes requirements, the contractor is pressured to change its method. The normative refers to professional bodies developing shared norms for an organisation within a specific field. Furthermore, Mimetics stems from uncertainty. When a clear course of action is unattainable, organisational leaders may determine that the best reaction is to mimic a peer they perceive to be successful (Mizruchi and Fein, 1999).

2.8 Technical Challenges

Although CV -CPM is feasible in theory, several functional computational issues still need to be resolved (Morgane et al., 2022). Furthermore, technical difficulties such as lack of integrity, durability, and reliability negatively affect innovative technologies (Schall Jr et al., 2018; Golizadeh et al., 2019). Computer vision follows the principle of "what you see is what you can analyse" (Fang et al., 2018a; Fang et al., 2018b); hence, data collection and analysis are the two main steps in this system. Table 2 adopted based on Sami et al. (2022), represents a summary of technical limitations for each technique of CV-CPM.

Table 2. Summary of technical limitations

Techniques	challenges
UAVs (Unmanned Aerial Vehicles)	▪ It needs proper operation ▪ Requires accurate path planning ▪ Requires obstruction avoidance planning ▪ Rotational and sudden angular movements cause blur.
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
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
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.

Structure from Motion (SfM)	▪ It takes more time to process larger vision datasets ▪ Les precise compared to other techniques.
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
Support Vector Machines (SVM)	▪ Not good for larger vision datasets ▪ Do not perform fairly when the dataset gets more noise
Simultaneous Localisation and Mapping (SLAM)	▪ Produces greater computational complexity in case larger dataset ▪ Image processing requires considerable time and memory
BIMs (Building Information Modelling) registration	▪ It does not work well with partly occluded patches in a 3D point cloud ▪ Registration of multiple point clouds causes the technical issue
Object recognition/matching	▪ No common method or technique is available to address a variety of construction. ▪ Features in terms of object recognition, matching, and tracking.

5 Discussion and Conclusion

5.1 Discussion

CV-CPM is a new technology, and the poor proficiency level is believed to be due to a lack of competencies and skills (Sami et al., 2022). Literature uncovered that the industry suffers from the low competency of construction workers and professionals (Oesterreich and Teuteberg, 2016). The review suggests that CV-CPM function is relatively better than the traditional CPM method, particularly in optimising schedules and real-time data collection capabilities. Similarly, the literature reflects that active on-demand data provide a fast and responsive assessment and assist in optimising schedules and resource planning. Change management" has also been mentioned as one of the advantages of CV-CPM as it can automatically detect and determine significant changes on-site. Automatic data collection was also ranked as the second advantage, as it can remove the extreme amount of manually data collection that causes human errors and diminish the data quality. in short, except for a few functions, the use level has shown relatively inadequate, and this reemphasises that the companies did not realise the full potential of CV-CPM in the UK (Vilde, 2021). High cost, lack of CV-CPM expertise and resistance to change are the most serious concerns for adopting CV-CPM. Because Individuals/companies perceive modern technologies transformation as a risk or consider the high cost of implementation as a serious burden since they are unclear about its benefits in terms of cost savings and investment requirements; hence, they perceive innovative technologies as costly to implement (Zhou et al., 2015; Oesterreich and Teuteberg, 2016; Dallasega et al., 2018; Demirkesen and Tezel, 2021). Lack of expertise is also listed among the important challenges for CV-CPM adoption. Given the conservative nature of the construction sector, it is unsurprising that respondents placed resistance to change as an important barrier.

In addition to the main concerns, lack of "client knowledge", "client demand", and "CV-CPM knowledge within the internal workforce" have also been noted a barriers to CV-CPM adoption. As discussed previously, lacking skills and knowledge are common issues, whether within a client or the internal workforce in construction; the absence of human resources with good proficiency in the computational field is also known as a barrier to implementing CV for CPM (Morgane et al., 2022). Client demand is also influential as construction companies will be more inspired by client demand (Kassem et al., 2012). Studies reported that unclear benefits directly affect technology adoption in the industry. The finding indicated that technological development, decision-making improvement, and competitive advantages are significant company incentives. Many authors claim that technological development is vital to boost competitive advantage. It has been theoretically justified and empirically confirmed that competition is an essential incentive for innovativeness (Mitropoulos and Tatum, 2000; Sayfullina, 2010). It motivates companies to keep their existing resilience and engage in further improvements to achieve more financial benefit.

Lastly, the role of the “partners/peers” is the most active driver to overcome the barriers of CV-CPM adoption, followed by when they realise a clear benefit and receive support from the vendor. This implies that the UK construction industry is willing to accept only when they see the result and benefits. It is believed that the influence of mimetic pressures on CV-CPM adoption can partially be mediated by client/owner/government sponsorship. As discussed in the previous paragraph, the respondent believes that companies welcome technology when they have clarity on the technological and financial benefits.

This study uncovered that respondents perceive CV-CPM as having a greater relative advantage, good compatibility with current practice, good trialability, and observability. Nevertheless, the complex process and the difficulty of learning and understanding have weakened the CV-CPM innovation diffusion process. The findings show that the "high cost and unclear benefits" are the top barriers. Moreover, looking at the institutional concept, "Our partners start using it" as a solution indicates that companies are only affected by mimetic pressure. In a broader sense, if "our partners/firms are not using CV-CPM, it can be a barrier, and when they start using it can be counted as a solution. This reveals that UK construction companies are uncertain about embracing CV-CPM due to their hesitation about the gains.

The review shows that the level of awareness of CV-CPM is fair among UK construction professionals, but they lack knowledge and skills. The method is better than the traditional approach. However, the use level is low irrespective of the company size. This may stem from the fact that the concept of a CV- CPM is still new, as evidenced by the research efforts in the form of proof of concepts, therefore, it is not surprising to be used mainly for change management and material tracking but not for progress measurement in UK construction. The review also investigated the challenges which include "cost of implementation, lack of expertise, and resistance to change" are the most serious barriers to adopting CV-CPM. It turned out that technological development, decision-making improvement, and competitive advantages are significant incentives, as technological advancement is essential to growing competitive benefits. The solutions to address the impediments of overall adoption are uncovered, which were "our partners start using it (mimicking peers) and found that the construction practitioners/companies operating in the UK are still not quite aware of the benefits and gains; therefore, they will adopt if "they see a "clear benefit" from CV-CPM implementation. It can be concluded from the study that implementation of the CV-CPM technology can accelerate the progress detection operations and data accessibility of UK construction sites. However, successful implementation has financial impacts and requires companies to have a solid strategy for unknown benefits and gains. To tackle the resistance to change issues, companies must work toward developing a changing culture or offer training to enhance the awareness of the workforce and prepare the industry for a soft transition.

The main contribution of this study is to provide construction professionals with a comprehensive list of barriers and incentives toward CV-CPM adoption. Industry practitioners might benefit from this research's findings and detailed evaluations to develop successful adoption and transformation strategies as CV-CPM can accelerate the progress detection and data accessibility for outcomes. This research is mainly based on the literature review, therefore, further data collection from construction professionals and incorporation of case studies might be more practical to monitor the practical implementation to assess better the challenges, possibilities, and drivers for CV-CPM in UK construction sites.

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