ISSN 1392-3730/eISSN 1822-3605

JOURNAL of CIVIL ENGINEERING and MANAGEMENT

2024
Volume 30
Issue 7
Pages 600–613
https://doi.org/10.3846/jcem.2024.20951

FACTORS AFFECTING IMPLEMENTATION OF COMPUTER VISION-BASED TECHNOLOGIES ADOPTED FOR MONITORING BUILDINGS CONSTRUCTION PROJECTS

Khalid Mhmoud ALZUBI[1,2], Wesam Salah ALALOUL[1✉], Marsail AL SALAHEEN[1,2], Bayan ALSAAIDAH[3], Muhammad Ali MUSARAT[1], Abdul Hannan QURESHI[1]

[1] *Department of Civil and Environmental Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610 Tronoh, Perak, Malaysia*
[2] *Department of Civil and Environmental Engineering, Al-husun University College Al-Balqa Applied University, Al- Salt 19117, Jordan*
[3] *Department of Computer Science, Prince Abdullah bin Ghazi Faculty of Information Technology and Communications, Al-Balqa Applied University, Salt 19117, Jordan*

Artile History:
- received 21 December 2022
- accepted 2 January 2024

Abstract. Construction monitoring in dynamic construction site environments poses significant challenges for construction management. To overcome these challenges, the implementation of computer vision (CV) technologies for construction project monitoring has gained traction. This study focuses on investigating the factors influence the successful implementation of CV technologies in monitoring construction activities within building projects. A comprehensive methodology was employed, including a systematic review of CV technologies implemented in construction and qualitative surveys conducted with construction experts. Additionally, a quantitative questionnaire was developed, and the collected data was analysed using structural equation modelling. The findings reveal the presence of 10 factors categorized into four constructs. Notably, all 10 factors demonstrate high value factor loadings and statistical significance, and among the four constructs (device, jobsite, environment, human), device (0.82) has the highest impact on the implementation of CV-based technologies on the construction site, followed by jobsite condition (0.62), human (0.61), and environment (0.51) came in the last place. By addressing these influential factors and mitigating their effects, construction stakeholders can enhance the implementation of CV technologies for monitoring construction sites. This study contributes valuable insights that inform the implementation and optimization of CV technologies in construction projects, ultimately advancing the field of construction management.

Keywords: automated monitoring, computer vision, factors, construction monitoring, automated technologies, structural equation modelling.

✉Corresponding author. E-mail: ***wesam.alaloul@utp.edu.my***

1. Introduction

The dynamic environment of construction sites (including various workers and machines operating simultaneously) makes managing the tasks of these sites a big challenge for project managers (Zhang et al., 2017). One of the most important tasks of construction managers is to keep track of and monitor various activities to ensure that the project fulfils expected production rates (Sherafat et al., 2020). Efficient data gathering, analysis, and monitoring of as-built status are key activities for the successful monitoring of construction projects (Alzubi et al., 2022c). The traditional methods for construction management (CM) have many limitations, such as being costly, inaccurate, and time-consuming, which may delay the information flow and result in poor decision-making (Alaloul et al., 2021a). Due to the inefficiency of old approaches, site managers must spend 30%–49% of their time collecting, processing, and evaluating data in order to decide on remedial measures and other relevant actions (McCulloch, 1997; Qureshi et al., 2022a). Automated monitoring (AM) systems allow the various aspects of construction activities and resources to be monitored timely and efficiently. Nowadays, it becomes necessary for each project to have an AM system that assures the timely and comprehensive delivery and visualization of the schedule, design, productivity rates, cost, and progress performance data in real-time, which will lead to preventing overruns and decision deviations (Alzubi et al., 2022c; Sherafat et al., 2020).

In construction projects, several AM technologies have been adopted for monitoring construction sites, such as computer vision (CV)-based technologies (Omar et al., 2018), laser scanning (LS) (Maalek et al., 2019), tags (Huang et al., 2021; Mohanty et al., 2020). Each of these technologies can be used to monitor specific types of activities with varying degrees of efficiency and accuracy (Omar et al., 2018). CV-based technologies have obviously gained in popularity among AM technologies for monitoring many aspects of construction sites, owing to the development of camera specifications, large storage databases, and Internet accessibility (Khosrowpour et al., 2014; Zhu et al., 2016). Due to the interdependence and complexity of construction activities, construction monitoring (CM) is regarded as one of the most difficult responsibilities (Alaloul et al., 2021a; Alzubi et al., 2021). Monitoring construction activities (MCA) is significant for the successful completion of projects and can enhance the competitiveness and sustainability of construction firms (Alaloul et al., 2021a; Alzubi et al., 2022b).

Although CV studies have achieved many valuable outcomes for MCA compared to traditional methods and other technologies, factors related to the adopted technologies, the challenging environment, and dynamic sites affect the implementation of CV studies in construction projects (Bügler et al., 2017; Alzubi et al., 2022c; Qureshi et al., 2022a; Sherafat et al., 2020). The implementation of CV-based technologies for MCA can be improved by investigating and taking these factors into consideration. Which will enhance the data gathering for updating construction progress effectively, and accurately (Alaloul 2021a; Alzubi et al., 2022b).

While there is a big chance for implementing CV-based technologies in construction (Bügler et al., 2017; Omar et al., 2018; Sherafat et al., 2020), domain-particular challenges have not been fully investigated. The low levels of AM adoption, including CV technologies, indicate that there is a clear need for additional discussions on factors affecting the effectiveness of CV-based technologies (Alaloul et al., 2021a; Ekanayake et al., 2021). This study focuses on CV-based studies as they have become popular among researchers for monitoring construction projects (Alzubi et al., 2021; Sherafat et al., 2020) and seeks to systematically investigate factors affecting the implementation of CV technologies that have been implemented for monitoring construction sites. This study aims to investigate the most significant factors affecting the implementation of CV technologies that have been adopted for MCA in building projects. This study is expected to assist construction firms in understanding the main factors affecting the implementation of CV-based models implemented for AM on buildings construction projects.

2. Literature review

Recently, several AM technologies (such as computer vision, laser scanning, and tagged-based studies) have been developed for monitoring various aspects of construction activities and operations (Ekanayake et al., 2021; Golparvar-Fard et al., 2015). Although these technologies have achieved many improvements compared to traditional monitoring methods, the challenging environment of construction sites affects the implementation of these technologies. There are many factors that affect the quality, implementation, and effectiveness of the implementation of these technologies for automated monitoring of construction activities. Some of these factors are related to the technology used for monitoring, including what is related to the mechanism of gathering data, and the others are related to the monitored site conditions and the surrounded environment. In the next subsections, factors affecting the implementation of some AM technologies are discussed briefly. Focussing on factors related to the implementation of CV technologies in buildings projects.

2.1. Computer vision technologies

CV-based technologies include the capturing, processing, and use of several algorithms for getting image data, CV-based technologies for monitoring are involved with replicating humans' vision and analysing images to evaluate the construction progress by computer hardware, software, and several algorithms (Alzubi et al., 2022a; Deng et al., 2020; Ekanayake et al., 2021). Additionally, CV refers to the process of automatically extracting data from visual inputs, such as images. The term "information" encompasses a wide range of possibilities, including but not limited to 3D models, determining the position of the camera, detecting and recognizing objects, as well as grouping and searching the content within images. The use of CV technologies in automated monitoring has shown cost and time savings, which has caught the attention of both construction professionals and academic researchers. These technologies have been successful in both indoor and outdoor monitoring when compared to other monitoring methods. The competitive advantages of accessibility of the Internet, high-resolution cameras, low cost, time, and ease of image capturing, and the advent of high-storage databases increase the employment of CV-based for CM (Deng et al., 2020; Qureshi et al., 2021). Although the consistent advent of cameras with high specifications and advancements in algorithms for image processing has improved the accuracy of CV-based technologies for CM, factors related to the dynamic environment of construction sites and other factors related to the technologies themselves limit the adoption of CV-based monitoring construction sites effectively (Deng et al., 2020; Hamledari et al., 2017).

These factors can be grouped into three major groups: jobsite conditions group, environment group, and mechanism of data gathering (device) group. The factors in the jobsite conditions group are related to the monitored construction site, such as occlusion and crowded sites. While the environmental factors are related to the surrounding environment and lighting conditions, the third group of factors are related to the adopted device for monitoring (camera specification, angle of capturing, image resolution, distance of the device to the monitored object, etc.) (Alzubi et al., 2022c; Qureshi et al., 2022a; Sherafat et al., 2020). These factors can restrict the ability of CV-based technologies to monitor different activities, resources, and operations of construction projects. For instance, difficulties in object detection and monitoring can occur when several components (fixed and dynamic resources) are present in captured images. Also, the monitoring of indoor construction operations is challenging for all AM technologies, including CV, because the progress is generally evaluated and connected to variants that occurred on a wall surface, and this results in capturing a high number of overlapping images and several objects have similarities in shape and colour for indoor elements (Deng et al., 2020; Ekanayake et al., 2021; Hamledari et al., 2017).

Furthermore, light fluctuations and changes are particularly associated with shadows, backlights, and missing artificial light sources during construction, resulting in complexity in extracting features and tracking construction resources and activities at regions of interest, reducing the overall effectiveness of CV-based and AM technologies. (Ekanayake et al., 2021; Qureshi et al., 2021). While camera movement uncertainties, camera specification and calibration, image resolution, capturing angle, and distance to object can all have an impact on the implementation of monitoring and detecting various construction objects (Alaloul et al., 2021a; Ekanayake et al., 2021). These factors must be eliminated to improve the monitoring, detection accuracy, and ability of CV-based systems in construction sites by reducing light fluctuation, developing and adjusting visual algorithms, and integrating different AM technologies for monitoring construction sites, etc. After reviewing the literature, 12 factors were found that affect the implementation of CV-based technologies as shown in Table 1.

It can be observed that there are many factors affecting the accuracy of tools used for monitoring construction sites. Some of them are common among the studies, such as occlusion, environment, and jobsite conditions (Alaloul et al., 2021a; Golparvar-Fard et al., 2015; Sherafat et al., 2020). While other factors are related to the adopted monitoring tool, like camera specification and calibration, the distance of the camera to the object, and the angle of capture (Golparvar-Fard et al., 2015; Luo et al., 2018). These factors affect the level of adoption of CV in construction sites, which indicates that there is a clear and significant need for additional discussions and up-to-date studies to eliminate the effect of these factors.

2.2. Laser scanning and tagged-based technologies

Laser scanning studies use a scanner to develop an as-built point cloud and compare it with an as-planned model; thus, the progress of a construction project can be evaluated (Ekanayake et al., 2021; Golparvar-Fard et al., 2015). Although the capability of laser scanning to acquire point clouds for projects with a high level of accuracy, some limitations reduce the level of adoption of laser scanning in construction, such as discontinuity of spatial information, slow warm-up time, and high cost (Golparvar-Fard et al., 2015; Alzubi et al., 2022c; Sherafat et al., 2020). Furthermore, tagged-based and laser scanning appear to be ineffective for indoor monitoring; laser scanning is unable to represent wall painting states because it cannot detect activity appearance changes (Deng et al., 2020; Ekanayake et al., 2021). In addition to that the implementation of LS in construction affected by many factors such as occlusions, number of scanned elements, scan distance, scanner resolution, number of scans, skills and experience of the operator, and weather (Golparvar-Fard et al., 2015).

While tagged-based technologies (such as global positioning system (GPS), radio frequency identification (RFID), and bar code) require attaching tags to each tracked construction resource; the tags can store the data of the tracked resource and send it using a network (Qureshi et al., 2022b). Due to the requirement for tags to be attached to the resources, data gathering is only suitable for a prefabricated structure (Deng et al., 2020), and it has limitations such as Poor indoor performance, high maintenance cost in the long term, creates discomfort feelings to workers due to physical attachment of tags, and do not identify the idle time (Alaloul et al., 2021a; Qureshi et al., 2022b). The implementation of these technologies in construction has been affected by several factors such as number of tags, signals overlapping, influence of signals by presence of liquids and obstacles, distance of device to object, and size of the jobsite (Alshibani, 2018; Mohanty et al., 2020; Sherafat et al., 2020).

Focusing on the implementation of CV technologies, the adopted methodology, results and discussion, and conclusion of the key findings of factors affecting the implementation of CV-based technologies are presented in the following sections.

3. Methodology

To achieve the objectives of this study, a mixed methodology was used. A literature review of automated monitoring in construction was implemented to identify the factors affecting AM in construction from previous studies using a systematic review; then, a qualitative survey was performed with industry experts and academicians to get the construction stakeholders' views on the study, and a pilot survey was also conducted with industry experts. Finally, the outcomes of qualitative and pilot surveys were used to develop the quantitative questionnaire and analyse its outcomes to identify the most significant factors affecting the implementation and effectiveness of CV-based technologies adopted for MCA. The collected data was analysed, and the most significant factors were identified. Figure 1 and the following subsections illustrate the performed methodology.

3.1. Identify the factors affecting AM technologies from the literature review

The literature review is defined as "a systematic, explicit, and reproducible method for identifying, evaluating and interpreting the existing body of recorded work" (Fink, 2005). The previous studies about CV-based studies in construction were investigated in depth using (PRISMA)

Table 1. Factors affecting CV-based technologies implemented in construction sites

Factors (literature)	modifications (interview)	Summary of factors	Description	References
Dynamic elements occlusion	No modification	Dynamic elements Occlusion (VDE)	Any moving elements that can block the image capturing (Element such as workers and vehicles).	Alaloul et al. (2021a), Bügler et al. (2017), Omar et al. (2018)
Fixed elements occlusion	No modification	Fixed elements Occlusion (VFE)	Element such as formwork, machineries, tower crane that block the view of capturing.	Bügler et al. (2017), Golparvar-Fard et al. (2015), Gong and Caldas (2011), Luo et al. (2018), Omar et al. (2018)
Crowded sites	No modification	Crowded sites (VCS)	Crowded sites by machines, labors, materials, and equipment, affect the objects detection and image quality.	Braun et al. (2020), Ekanayake et al. (2021), Konstantinou et al. (2019), Luo et al. (2018), Sherafat et al. (2020)
Lightning condition	No modification	Lightning Condition (VLC)	The change in the light degree during the day (daylight fluctuations), because of the sunlight, shadows, etc.	Bügler et al. (2017), Omar et al. (2018), Sherafat et al. (2020)
Weather	Consider temperature and humidity	Weather (VW)	The effects of the climate changes on the capturing images (rain, snow, dust, fog, wind, temperature, humidity).	Bügler et al. (2017), Deng et al. (2020), Sherafat et al. (2020)
Calibration of camera	No modification	Calibration of camera (VCC)	It is the process of determining specific camera parameters to complete operations with specified measurements.	Bügler et al. (2017), Mneymneh et al. (2018), Omar et al. (2018)
Image Resolution	No modification	Image Resolution (VIR)	Refers to how many pixels are displayed per inch of an image. Higher resolution will have a clear point cloud.	Bügler et al. (2017), Seo et al. (2015)
Number of captured images	No modification	Number of captured images (VNC)	Number of captured images would affect the accuracy of 3D point cloud data.	Alzubi et al. (2022a), Golparvar-Fard et al. (2015), Hamledari et al. (2017)
Specification of camera	No modification	Specification of camera (VS)	Include the number of megapixels, aperture, focal length, sensor size, zoom type and methods of stabilization and focusing system, etc.	Bügler et al. (2017), Gong and Caldas (2011), Qureshi et al. (2022b), Omar et al. (2018)
Distance of camera to object	No modification	Distance of camera to object (VD)	The distance between the camera and the object changes the scale of the monitored object.	Bügler et al. (2017), Mneymneh et al. (2018), Omar et al. (2018)
Capturing angle	No modification	Capturing angle (VCA)	The angle capturing between the camera and the object changes the scale of the tracking objects.	Bügler et al. (2017), Omar et al. (2018)
Human intervention	No modification	Human Intervention (VHI)	The quality of the images affected by the personal skills and experience.	Alzubi et al. (2022b), Omar et al. (2018)
–	Consider overlapping as a factor	Overlapping (VO)	Overlapping area between two adjacent images.	Semi-structured interview
–	Consider ground control points as a factor	Ground control points (VGCP)	They are points on the ground with known coordinates.	Semi-structured interview
–	Consider drone speed as a factor	Drone speed (VDS)	Speed of drone movement affect the quality of capturing.	Semi-structured interview

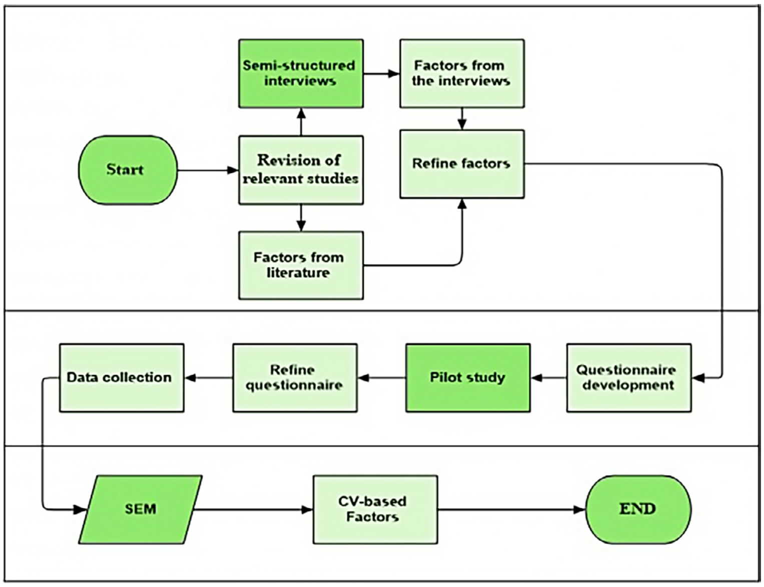

Figure 1. Flow chart for the research methodology

protocol guidelines to extract the most related studies regarding the challenges and factors affecting implementation of the adoption of CV-based technologies in building construction sites. The scope was limited to the studies of CV-based adopted for MCA in building projects, published in WoS and SCOPUS databases, in English, and from 01-01-2012 to 01-01-2022. This focus is consistent with the majority of studies in the domain of automated monitoring, which have predominantly covered building projects as case studies. By concentrating on building projects, the study aims to provide a more in-depth exploration of the achievements and challenges in the implementation of computer vision technologies for monitoring in this specific context (Alaloul et al., 2021b; Álvares & Costa, 2018).

In the WoS, the advanced search was "TS = ((computer) AND (vision) AND (monitor) AND (factor OR variable OR limitation OR challenge) AND (construction OR building) NOT (infrastructure or highway or tunnel))". The number of outcomes of this search was 140, which, based on the study scope, was refined to 8 results. The keywords inquiry for the Scopus was developed as "TITLE-ABS-KEY((computer) AND (vision) AND (monitor) AND ((factor) OR (variable) OR (limit*) OR (challenge)) AND ((construction) OR (build*))". 81 results were provided, which were refined to 7 results. A total of 15 articles were retrieved for full-text screening after removing the duplications and screening titles, abstracts, and full text. Table 1 shows the collected factors from the literature.

3.2. Qualitative survey

To understand and validate the identified factors from the literature, semi-structured interviews were done with 17 academicians and construction professionals, as the literature suggests a minimum sample size for interviews to be between 5 and 50 semi-structured interviews (Qureshi et al., 2022b). The main goals of the interviews were to understand the views of the experts about the CV-based monitoring method and validate the systematic review outcomes related to the factors and identify the relations among the factors. The interviews focused on the acquisition viewpoints of the interviewees on the value of the factors extracted from the literature. The interview process includes the categorization and merging of the identified factors.

3.3. Quantitative survey

The quantitative research was conducted where a questionnaire survey was the main tool to obtain the required data. A questionnaire survey was developed according to the modified factors using a Likert scale of 1–5 where (Strongly Agree = 5, Agree = 4, Neutral = 3, Disagree = 2, Strongly Disagree =1). The questionnaire involved three main sections. The first section is the introduction, which includes a brief explanation of the study's purpose. The second section is the respondents' profile, which includes information related to the respondents, such as their level of education and years of experience. In the third section, which is the body of the study, the survey was sent by email to academicians and construction experts working in Jordan and the Malaysian construction industry.

Before the distribution, a pilot survey was conducted with 12 experts to ensure the reliability and significance of all items in the questionnaire. The literature provides guidelines regarding the pilot survey sample size, i.e., 10 to 12 (Saunders et al., 2009; Sekaran & Bougie, 2016). In response to the experts' valuable input, several modifications were made to improve the questionnaire. Firstly, certain questions that were not clear were rewritten to enhance clarity and ensure respondents' better understanding. Additionally, the survey was carefully reviewed and condensed to remove any redundant or unnecessary questions, streamlining the questionnaire to focus on the most relevant aspects of the research. These modifications aimed to enhance the quality of data collected and improve the overall user experience for the participants. As a result of these revisions, the questionnaire was prepared for distribution.

To represent the research population, determining the properly targeted sample size is essential. To calculate sample size (Israel, 1992) provided the following formula:

$$n_0 = \frac{Z^2 pq}{e^2}, \quad (1)$$

where, n_0 represents the infinite population sample size, Z – the normal curve abscissa that cuts off an area α at the tails, and it is taken as 1.96 for a 95% confidence level, q is $1 - p$; maximum variability is obtained when $p = 0.5$, where p is an attribute's proportion that is present in the population, and e – desired level of precision and is taken as 0.07.

4. Results and discussions

This study focuses on building projects and the adopted CV models used for monitoring various aspects of construction sites. After reviewing the literature, 12 factors were found that affect the implementation of CV-based technologies. After considering the comments of the interviewees, three new factors were added. As a result, the total extracted factors from literature and semi-structured interviews are 15 factors, as presented in Table 1. The next subsections represent the outcomes of the qualitative and quantitative surveys.

4.1. Qualitative research outcomes

In the semi-structured interview, respondents were provided with a list of the factors that were extracted from the literature and were asked to express their opinions about them. Table 1 shows the final list of the factors (15 factors) after considering the comments of the interviewees and merging the factors list from the literature with the factors from the semi-structured interviews. The questionnaire was shared with 17 academicians and industry professionals, where a minimum sample size of 5 to 50 for semi-structured interviews has been suggested in the literature (Qureshi et al., 2022b). The following Figure 2 shows years of experience and level of education for the interviewees, which shows that 76% (13) of interviewees have more than (10) years of work experience. Among them, 29% (5) were above 15 years.

The review and semi-structured interviews were used and highlighted three categories, i.e., jobsite condition (3 factors), device (camera) (10 factors), and environment (2 factors). To reinforce the credibility of the new factors introduced in the study, a comprehensive approach was taken to ensure the appropriateness of their categorization. In the semi-structured interviews conducted with participants, the categories, including the new factors (VO, VGCP, VDS), were presented and discussed. The interviewees were actively engaged in the categorization process, providing valuable feedback. Importantly, no objections were raised regarding the categorization of these new factors, affirming the clarity and relevance of their placement within the identified constructs.

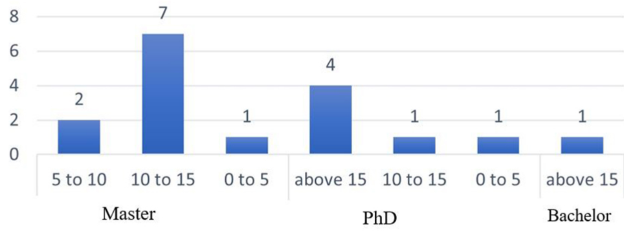

Figure 2. Interviewees' demography

NVivo, a qualitative data analysis software, was used to analyse the collected feedback for content analysis. A content analysis was performed to emphasize the key points made by the interviewees. NVivo coding was utilized to extract significant comments from the interview scripts. Figure 3 depicts the derived NVivo model from the semi-structured interview content, which demonstrates the primary categories and factors influencing CV-based technologies.

4.2. Quantitative research outcomes

To ensure adequate representation of the research population, the authors employed a well-established random sampling technique to determine the appropriate sample size. In line with this, the sample size calculation was performed using the formula proposed by Israel (1992), which is widely recognized for estimating sample sizes in survey research. By applying Eqn (1), the minimum required sample size for the target population was determined to be 196 responses. To ensure robust data collection, a total of over 700 questionnaires were distributed via email, specifically targeting construction engineers and academic experts from Jordan and Malaysia. This large distribution was carried out using random sampling, where individuals were selected from the target population at random, ensuring that each individual had an equal chance of being included in the survey. This approach enhances the representativeness of the sample and improves the generalizability of the findings.

The total number of collected responses was 240, which were analysed using the IBM SPSS-AMOS software, which is a powerful structural equation modelling (SEM) software that assists research by expanding standard multivariate analysis methods such as regression, factor analysis, and correlation (Arbuckle, 2011). Before analysing the data, it was checked to ensure that there were no missing values, errors, or respondent misconduct. Among the 240 received responses, five responses were deleted due to the respondents' misconduct, because there was no variance among the responses across the survey. Figure 4 represents the respondents' demographic profile.

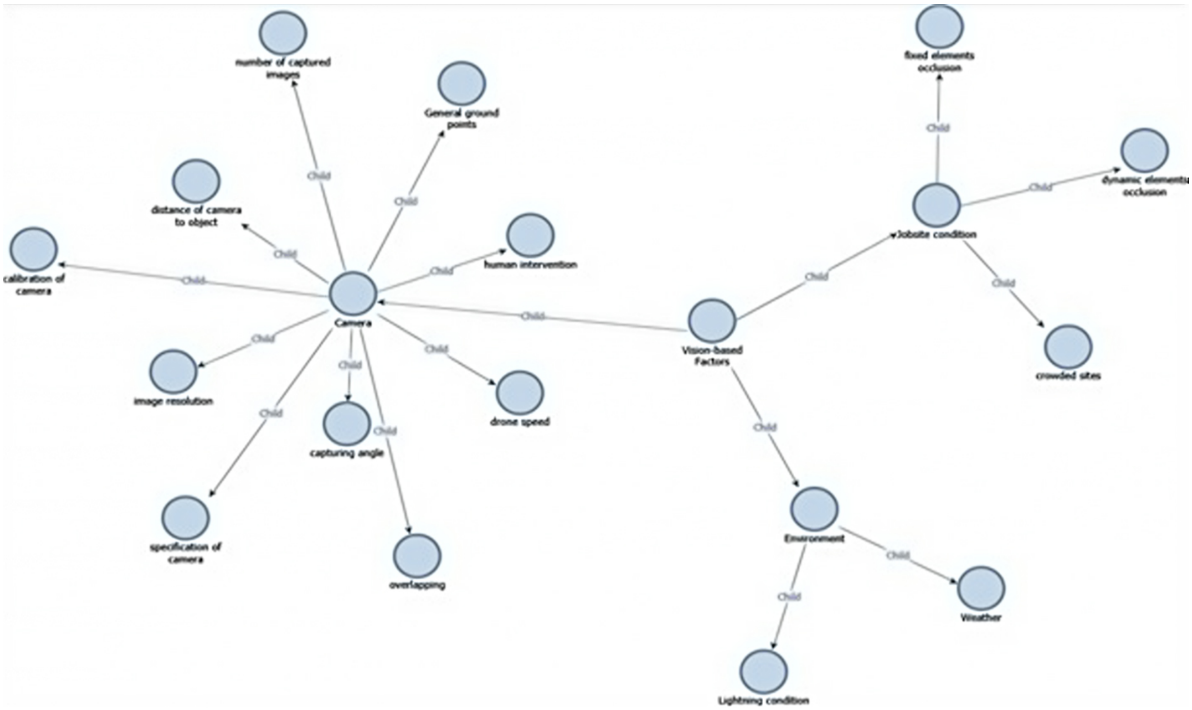

Figure 3. Extracted parameters for CV-based factors from content analysis

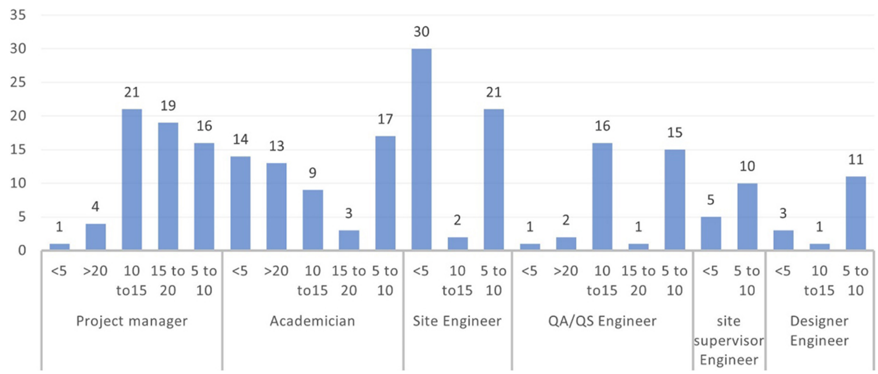

Figure 4. Demography profile of respondents (job position and years of experience)

Overall, among the remaining 235 responses, 56 responses (23.8%) were collected from academia and 179 responses (76.2%) from construction industry professionals. Also, 77% of respondents (181) have more than 5 years' experience. Among them, 18% of participants have experience more than 15 years.

Cronbach's alpha is a measure of internal consistency or reliability for a scale or test (Demir et al., 2016; Taber, 2018). This coefficient assesses how well the items in a scale or test measure the same underlying construct. In other words, it gauges the degree to which different items in a survey or test are correlated and contribute consistently to measuring the intended concept. Cronbach's alpha ranges from 0 to 1, with higher values indicating greater internal consistency. Commonly, a threshold of 0.7 is considered acceptable, and values above 0.9 are deemed excellent (Demir et al., 2016; Qureshi et al., 2022b; Taber, 2018). Researchers use Cronbach's alpha to ensure that the items in their survey or test are reliable and effectively measure the construct of interest (Taber, 2018; Tavakol & Dennick, 2011). When designing a questionnaire to explore various factors, it's crucial to ensure that the items or questions included in the survey are internally consistent, that is, they measure the same underlying construct or idea. By calculating Cronbach's alpha for the responses of a questionnaire, the survey items align with each other can be evaluated. A high Cronbach's alpha indicates that the items are measuring the same or very closely related aspects of the construct, providing a level of confidence in the reliability of the survey instrument. This is essential for drawing meaningful conclusions from the collected data and ensuring that the survey effectively captures the required data to evaluate the factors influencing the implementation of CV technologies in construction.

The collected data, i.e., 235 responses, were evaluated using Cronbach's alpha for internal consistency. The value of Cronbach's alpha was found to be 0.889 for the collected data, which reflects a very good value.

SEM was performed to find the significant factors affecting CV-based technologies adopted for MCA.

4.2.1. SEM

SEM is a flexible multivariate statistical tool used to test hypotheses concerning relationships between latent and observable variables (Ahmad et al., 2016). SEM can be performed either on the theory-based conceptual frameworks or frameworks developed based on exploratory factor analysis (EFA) (Qureshi et al., 2023). The SEM is made up of two models. The first, known as the measurement model, does confirmatory factor analysis (CFA) and links the constructs by measuring variables to latent factors by assessing their reliability and validity according to set standards to develop the model. The second model assesses the associations between latent components by calculating variances, testing hypotheses, and fine-tuning the model as needed and it is known as a structural model (SM) (Awang, 2012). The following subsections describe the two models (CFA and SM).

4.2.1.1. Exploratory factor analysis (EFA)

EFA is commonly employed as an initial step in research to examine the underlying constructs and gain preliminary insights into the relationships between measured variables and latent factors (Dragan & Topolšek, 2014). Its primary purpose is to uncover patterns and structures within the data without relying on preestablished hypotheses. EFA serves as a valuable tool to provide guidance for further research, particularly in informing the development of a more specific and testable theory. The EFA involves three key stages (suitability of data, factor extraction, and factor Rotation and Interpretation) (Dragan & Topolšek, 2014; Ogunsanya et al., 2022).

The first stage is suitability of data which involves evaluating the data for sample size adequacy and the strength of correlations among variables. The consensus suggests that a larger sample size is preferable, with recommendations ranging from at least 150 to 300 cases (Dragan & Topolšek, 2014; Ogunsanya et al., 2022; Pallant, 2020), in this study the data were collected from 235 responses. The correlation matrix is examined for coefficients greater than 0.3 to ensure adequate interrelationships among variables (Dragan & Topolšek, 2014; Ogunsanya et al., 2022). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity are employed to confirm these conditions.

The second stage is factor extraction which focuses on identifying the minimum number of factors necessary to represent the interrelationships among variables. Various techniques, such as principal component analysis, principal factors, image factoring, and generalized least squares, can be used for factor extraction (Dragan & Topolšek, 2014; Ogunsanya et al., 2022; Pallant, 2020). Principal component analysis is commonly employed which is often assessed through methods like Kaiser's criterion, scree test, or parallel analysis (Dragan & Topolšek, 2014; Ogunsanya et al., 2022; Pallant, 2020). The Kaiser's criterion is used in this study.

The third stage is factor rotation and interpretation which enhances the clarity of components without changing the underlying solutions. It presents components as variable clusters used techniques like varimax, quartimax, and equamax (Dragan & Topolšek, 2014; Ogunsanya et al., 2022; Pallant, 2020). The varimax technique is employed in this study for factor rotation.

Factor analysis is considered appropriate when the KMO exceeds the satisfactory minimum threshold of 0.5 and ideally reaches 0.8 or higher (Dragan & Topolšek, 2014; Williams et al., 2010). A recommended KMO cutoff value is greater than or equal to 0.70 (Dragan & Topolšek, 2014). Bartlett's test, with a significance level below 0.05, supports the suitability of the factor model, indicating potential correlations among variables and the formation of reasonable clusters of factors (Hair Jr et al., 2021; Leguina, 2015). As shown in Table 2, KMO value is 0.811 which is bigger the desirable value of 0.8. While the Bartlett's test of sphericity is 1902.262 with an associated significance of 0.000 < 0.05.

Before conducting principal component analysis, communalities extracted for each variable were assessed. Communalities represent the total shared variance of an original variable with all other variables included in the factor analysis. An average communality above 0.60 is considered necessary for reliable results and interpretations, and the conventional rule suggests that a potentially significant variable should have an extraction value greater than 0.50 at the initial iteration (Hair Jr et al., 2021; Ogunsanya et al., 2022). Accordingly, three variables (VCC, VDS, VGCP) were found with communalities values less than 0.5 and have been extracted the further analysis. Accordingly, the EFA was repeated without including these factors. The new value of KMO and Bartlett's test of sphericity is shown in Table 2. The KMO value is 0.763 which is bigger than the cutoff value (0.7).

Table 3 shows the communalities values after removing the three factors and it can be shown that all of the values of the remaining variables (12) are above 0.5, indicating the importance of these variables for further analysis.

Table 4 shows that four factor components were obtained and explaining a total of 75.284% of the variances which is above the recommended total explained variance value (50%) (Dragan & Topolšek, 2014; Ogunsanya et al., 2022; Pallant, 2020). Also, the rotated component matrix in Table 4. Shows four distinct components as each variable dominantly belonged to a unique factor. Three of extract-

Table 2. KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.763
Bartlett's Test of Sphericity	Approx. Chi-Square	1649.984
	df	66
	Sig.	0.000

Table 3. Communalities values (extracted method: Principal Component Analysis)

Communalities		
	Initial	Extraction
VDE	1.000	0.779
VFE	1.000	0.752
VCS	1.000	0.667
VLC	1.000	0.972
VW	1.000	0.973
VIR	1.000	0.839
VS	1.000	0.818
VO	1.000	0.549
VCA	1.000	0.670
VNC	1.000	0.669
VD	1.000	0.754
VHI	1.000	0.592

ed component (Jobsite, Environment, Device) were named according to the previous mentioned interviews, while the last component (Human) was named according to the definition of the variables and their relation to the human intervention). The first component is Device which contains four variables (VIR, VS, VO, VCA), the second component is Human contains three variables (VNC, VD, VHI), the third component is Jobsite and contains three variables (VDE, VFE, VCS), and the fourth is Weather component which contains two variables (VLC, VW).

This multi-step validation process, involving EFA, direct input from interviewees, and expert evaluations, adds robustness to the categorization of the new variables, supporting their integration into the study's framework (Ho et al., 2012; Patton, 2014; Qureshi et al., 2023).

The extracted categories and variables from the literature, semi-structured interview, and the EFA were further analysed using SEM as shown in the following sections.

4.2.1.2. First model (CFA)

The measurement model for performing CFA was constructed based on the acquired data to test the model's reliability and validity. A factor loading of 0.7 is commonly regarded as adequate for latent value contribution, and anything less is normally removed from the CFA model (Hair Jr et al., 2017). In this study, observed variables with factor loadings below 0.6 were eliminated, resulting in the final well-fitted measurement model. Furthermore, some researchers have employed error correlations between variables to enhance model fit (Awang, 2012; Qureshi et al., 2023). From the 12 variables extracted from the EFA, one variable (VO) from the Human category was deleted since the value of it is factor loading was less than 0.6 as shown in Figure 5.

In order to assess the model fit, the derived measurement model was evaluated for reliability and validity. Where reliability is defined as "the degree to which the measurement model is trustworthy in measuring the desired latent components", and construct reliability (CR) is the evaluation criterion. While validity is defined as "the model's ability to measure what is supposed to be measured for a construct" (Said et al., 2011).

Convergent validity (AVE) and goodness of fit (GOF), i.e., construct validity, are the key validity evaluation criteria. Table 6 provides the measurement model's validity and reliability findings, and Table 7 shows the GOF for the CFA model together with the generally inferred standard testing criteria (Alaloul et al., 2020b).

Based on CR and AVE results, the CFA model meets the reliability and validity requirements. Furthermore, the overall fit of the baseline model was tested using multiple GOF, which is an important step in any SEM. The CFA model passed the GOF according to the criteria, as indicated in Table 7, which increases the model credibility.

Table 4. Total variance explained

Total variance explained									
Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.616	38.467	38.467	4.616	38.467	38.467	2.603	21.689	21.689
2	1.883	15.693	54.160	1.883	15.693	54.160	2.315	19.289	40.978
3	1.385	11.541	65.701	1.385	11.541	65.701	2.142	17.852	58.830
4	1.150	9.583	75.284	1.150	9.583	75.284	1.975	16.454	75.284
5	0.579	4.823	80.107						
6	0.575	4.792	84.900						
7	0.540	4.497	89.396						
8	0.455	3.790	93.186						
9	0.339	2.826	96.012						
10	0.248	2.064	98.076						
11	0.189	1.578	99.654						
12	0.042	0.346	100.000						

Note: Extraction Method: Principal Component Analysis.

Table 5. Rotated component matrix

Rotated component matrix[a]				
	Component			
	1	2	3	4
Jobsite				
VDE			0.837	
VFE			0.834	
VCS			0.755	
Weather				
VLC				0.960
VW				0.957
Device				
VIR	0.877			
VS	0.861			
VO	0.669			
VCA	0.622	0.531		
Human				
VNC		0.780		
VD		0.845		
VHI		0.708		

Notes: Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization; a – Rotation converged in 5 iterations.

Table 6. Reliability and validity outcomes

Constructs	AVE > 0.5	CR > 0.6
Device	0.535	0.81
Environment	0.59	0.73
Jobsite	0.52	0.68
Human	0.51	0.78

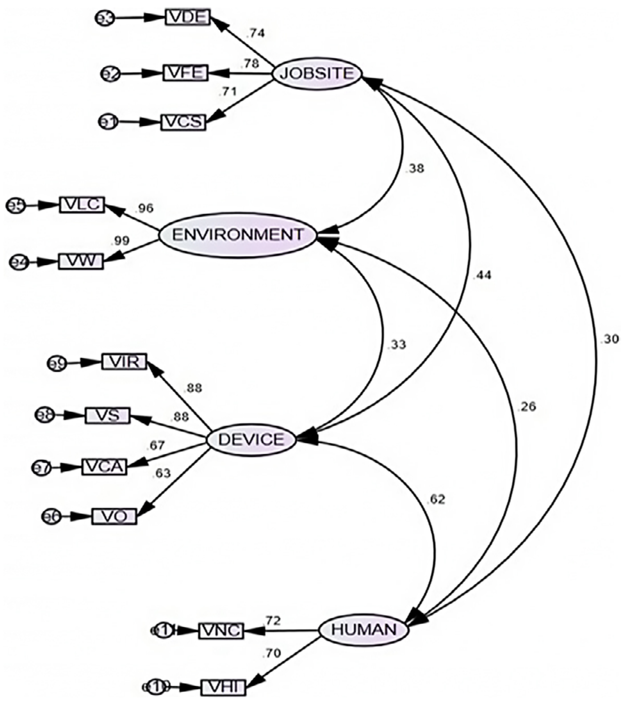

Figure 5. CFA model

4.2.1.3. Second model (SM)

The structural model (SM) was generated based on the model fit of the measurement model, as shown in Figure 6, and tested for model fit using the GOF indices, as given in Table 8. The focus is on understanding the challenges related to the implementation of CV technologies in the construction industry. The model fit indices for the developed SM model shows a good fit. The attained SM highlights eight factors within three constructs (jobsite condition, device, and environment) that affect the implementation of CV-based technologies adopted for monitoring construction activities. Notice that all the 8 factor loadings are high in value and statistically significant (0.62–0.99), and among the constructs (device, jobsite, environment, human), device (0.82) has the highest impact on the implementation of CV-based technologies on the construction site, followed by jobsite condition (0.62), human (0.61), and environment (0.51) came in the last place. Also, the model shows that the specification of camera (VS) with factor loading (0.89) has the highest impact among other factors within the device category; weather (VW) with (0.99) has the highest impact within the environmental category, crowded sites variable (VCS) has the highest impact within the jobsite condition category, and number of captured images (VNC) has the highest impact within the human category. Understanding these factors is essential for devising strategies to mitigate challenges and enhance the robustness of CV-based technologies in construction monitoring. Overcoming these limitations may involve advancements in device technology, adaptive algorithms for dynamic environments, and resilient models that can operate effectively under varying environmental conditions.

The following Table 9 shows the factors that were maintained and deleted after developing the SEM.

Table 7. GOF indices for the CFA model

Category	Index Name	Index	Attained Values	Acceptance criteria
Absolute Fit Indices	Discrepancy Chi square	Chisq	33.2	p > 0.01
	Goodness of Fit Index	GFI	0.939	> 0.90
	Root Mean Square of Error Approximation	RMSEA	0.073	< 0.08
Incremental Fit	Comparative Fit Index	CFI	0.967	> 0.90
Indices	Tucker-Lewis Index	TLI	0.952	> 0.90
Parsimonious Fit	Chi Square/Degree of freedom	Chisq/df	2.26	< 3

Table 8. GOF indices for the SM model

Category	Index	Acceptance criteria	Attained Values
Absolute Fit Indices	Chisq	p > 0.01	81.37
	RMSEA	<0.08	0.079
	GFI	>0.90	0.936
Incremental Fit	CFI	>0.90	0.963
Indices	TLI	>0.90	0.95
Parsimonious Fit	Chisq/df	<3	2.466

These outcomes are consistent with several researchers' notes, which indicate that the specification of the device, the resolution of captured images, and the weather have to be taken into consideration while monitoring construction sites using CV-based technologies (Bügler et al., 2017; Qureshi et al., 2022b; Mneymneh et al., 2018). Also, these outcomes are compatible with the idea that CV-based technologies include capturing, processing, use of several algorithms for getting 2D or 3D image data, replicating the vision of humans, and analysing the collected images to evaluate the construction progress (Ekanayake et al., 2021).

In addition to the factors identified in this study, there are other important considerations that can significantly impact the implementation and effectiveness of CV-based technologies for construction monitoring. Two such factors are variations in the appearance of objects and variation in task sequence and methods. The appearance of objects in construction sites can vary due to lighting conditions, weather changes, occlusions, and other factors. These variations can pose challenges to the detection and recognition algorithms employed in CV models. Another crucial factor is the variation in task sequence and methods within construction operations. Different construction tasks may follow unique sequences and employ distinct methods, making it necessary to adapt CV technologies to handle such variations effectively. Considering these additional

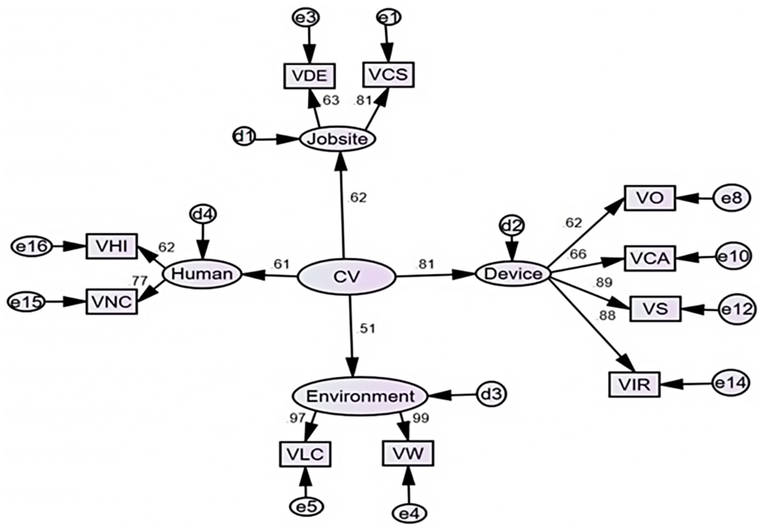

Figure 6. SM model for factors affecting CV-based technologies

Table 9. Factors affecting CV-based technologies

Category	Factors (literature)	Modifications (interviews)	Summary of factors	SEM outcomes
Jobsite condition	Dynamic elements occlusion	No modification	Dynamic elements occlusion (VDE)	Maintained
	Fixed elements occlusion	No modification	Fixed elements occlusion (VFE)	Deleted
	Crowded sites	No modification	Crowded sites (VCS)	Maintained
Environment	Lightning condition	No modification	Lightning condition (VLC)	Maintained
	Weather	Consider temperature and humidity	Weather (VW)	Maintained
Device	Calibration of camera	No modification	Calibration of camera (VCC)	Deleted
	Image resolution	No modification	Image Resolution (VIR)	Maintained
	Specification of camera	No modification	Specification of camera (VS)	Maintained
	Capturing angle	No modification	Capturing angle (VCA)	Maintained
	–	Consider overlapping as a factor	Overlapping (VO)	Maintained
	–	Consider ground control points as a factor	Ground control points (VGCP)	Deleted
	–	Consider drone speed as a factor	Drone speed (VDS)	Deleted
Human	Human intervention	No modification	Human Intervention (VHI)	Maintained
	Number of captured images	No modification	Number of captured images (VNC)	Maintained
	Distance of camera to object	No modification	Distance of camera to object (VD)	Deleted

factors and their significance, it is evident that further research is needed to delve deeper into their effects on CV-based technologies in construction monitoring. By exploring techniques to address variations in object appearance and developing robust methods for handling diverse task sequences, researchers can enhance the performance and applicability of CV technologies in construction monitoring. This opens avenues for future studies to advance the understanding and application of CV-based approaches in the construction domain.

Figure 7 shows the conceptual framework of this study; the implementation of CV-based technologies can be improved by taking the factors affecting the implementation of CV for monitoring construction sites into consideration. This will enhance the data gathering for construction progress and monitoring different aspects of construction sites effectively and timely. This will result in more effective judgments and the ability to take corrective actions in a timely manner, reducing errors and cost overruns. All of these parameters increase the likelihood of construction projects being completed successfully.

5. Conclusions

Among automated monitoring technologies, CV-based studies have gained popularity in monitoring construction sites, due to advancements such as high-resolution cameras, internet accessibility, and large storage databases. However, the implementation of CV-based technologies in construction sites are influenced by various factors. This study aimed to investigate these factors comprehensively by adopting a mixed methodology.

First, a systematic literature review was conducted to examine previous studies that utilized CV-based technologies for monitoring different aspects of construction operations and to identify the factors influencing their implementation. Additionally, a qualitative study was performed to gather insights from construction stakeholders. Finally, a quantitative analysis using SEM was employed to find the factor loading for the identified factors.

The SEM results revealed 10 variables within four constructs (jobsite condition, device, human, and environment) that significantly impact the implementation of CV-based technologies deployed on construction sites. Notably, all 10 variables demonstrated high factor loadings and statistical significance. Among the constructs, the device construct exhibited the highest impact (0.89), followed by jobsite condition construct (0.62), human construct (0.61) and environment construct (0.51).

Furthermore, the analysis identified specific variables within each construct that have the most significant influence. For instance, "Specification of camera" (VS) within the device category showed the highest impact, "Weather" (VW) within the environment category exhibited the highest impact, "Crowded sites" (VCS) had the highest impact within the jobsite condition category, and "Number of captured images" (VNC) had the highest impact within the human category.

Based on these findings, it is crucial to address these influential factors to enhance the monitoring and detection implementation of CV technologies on construction sites. Recommendations include selecting the most suitable camera specifications for construction sites, mitigating light fluctuations, refining and optimizing visual algorithms, and integrating various automated monitoring technologies for comprehensive site monitoring.

This study contributes to the understanding of factors affecting the implementation of CV-based technologies in construction site monitoring. By identifying and prioritizing these factors, construction stakeholders can make informed decisions and implement strategies to improve the effectiveness and reliability of CV technologies in construction site monitoring and management.

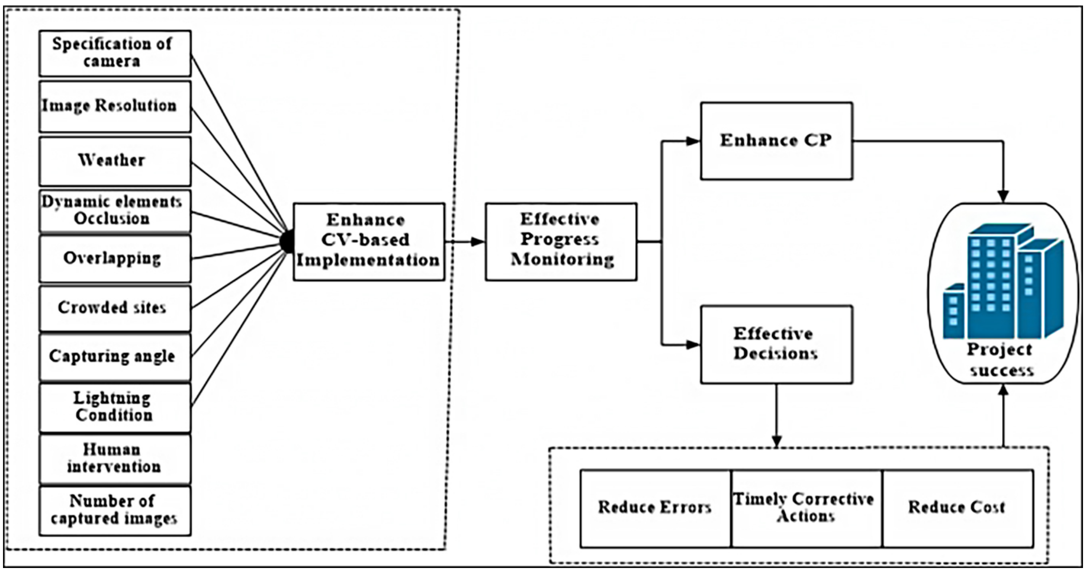

Figure 7. Conceptual framework

This study was limited to the factors mentioned in Table (1), which extracted from Scopus and WoS databases using the systematic review and according to the semi-structured interview. The significance of additional factors that might be not mentioned in this study, such as variations in the appearance of objects and variation in task sequence, cannot be overlooked. Such these factors have been highlighted in previous studies as influential elements affecting the implementation and performance of CV models in real-world construction scenarios.

Future research endeavours should explore such these factors more comprehensively to enhance the understanding and application of CV technologies in the construction domain. By highlighting the relevance of other factors that might influencing CV applications in construction industry, further exploration in subsequent studies is encouraged to broaden insights and improve the overall performance of CV-based technologies in construction monitoring.

Acknowledgements

The authors would like to thank the Universiti Teknologi PETRONAS (UTP) for the support from the (cost centre 015MD0-178) awarded to Wesam Salah Alaloul.

Competing interests

No competing interests to declare by authors.

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