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RESEARCH ARTICLE-CIVIL ENGINEERING

Characteristics-Based Framework of Effective Automated Monitoring Parameters in Construction Projects

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Abstract

The construction industry is moving toward digitalization, and technologies support various construction processes. In the automated construction progress monitoring domain, several modern progress measurement techniques have been introduced. However, a hesitant attitude has been observed toward its adoption. Researchers have highlighted lack of theoretical understanding of effectual implementation is one of the significant reasons. This study aims to analyze general technological parameters related to automated monitoring technologies and devise a theoretical-based conceptual framework explaining the aspects affecting the adequate operation of automated monitoring. The study has been executed by following a systematic inline process for the identification of effective parameters, which include a structured literature review, semi-structured interviews, pilot survey, questionnaire survey, and structural equation modeling (SEM)-based mathematical model. A refined conceptual framework has been devised with 21 effective parameters under five significant categories, i.e., "Target Object," "Technical," "External Interference," "Occlusions," and "Sensing." A knowledge framework has been established by adopting the SEM technique, which is designed on the characteristics-based theme. This conceptual framework provides the theoretical base for practitioners toward the conceptual understanding of automated monitoring processes related to technological parameters that affect the outcomes. This study is unique as it focused on the general criteria or parameters that affect the performance or outcomes of the digital monitoring process and is easily understandable by the user or operator.

Keywords Effective monitoring factors · Automated monitoring framework · Detection technologies · Exploratory factor analysis · Confirmatory factor analysis

1 Introduction

Progress monitoring is a procedure to review, track, and orchestrate the performance of construction projects [1], referring to comparing and inspecting the daily on-site progress of work activities with the constructed plan and validating the projected performance [2]. Progress monitoring of the construction project is crucial and enables construction managers to make timely decisions based on vital inputs [3]. In the success of construction projects, effective progress measurement is a critical key parameter [4]. Effective monitoring strategies may turn a defunct project into a successful completion [2]. Erudition of the actual progress state contributes to critical decision making, as it allows the project team to accomplish the tasks probably close to achieving the targeted outcome, regardless of the deviated project schedule [5]. Unreliable conventional methods and lack of confidence in gathering relevant data lead to counterproductive decisions

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and have been highlighted as two main reasons for inadequate tracking of construction projects [6]. Unfortunately, the construction sector is still influenced by time-consuming, manual conventional monitoring approaches, which are more prone to error due to human involvement [7, 8]. Adopting such traditional methodologies is inefficient, and 20–30% of extra efforts are wasted by project teams, which may cost the project up to 10% of the budgeted cost, as late defect detections lead to rework [9]. Moreover, ineffective progress monitoring may provide unrealistic progress details and ineffective resource utilization due to project managers' flawed judgments [10]. This emphasizes the importance of selecting a righteous monitoring methodology for efficient data collection and reduced risk. Modern digital monitoring technologies have overcome these aforementioned concerns [11]. Implementing advanced digitized data-acquisition-detection technologies is improving the performance of monitoring practices, especially for as-built construction projects [12]. Monitoring technologies are catered under imaging techniques (videogrammetry, laser scanning, and photogrammetry), geospatial techniques (geographic information system (GIS) and global positioning system (GPS), ultra-wideband (UWB), radio frequency identification (RFID), and barcode), and virtual reality/augmented reality techniques (VR/AR) [13]. This technological evolution in the construction sector has led to remarkable innovations such as building information modeling (BIM) [14]. Four-dimensional BIM models are believed to be significant for automated monitoring and analyzing the construction sequences [15]. Moreover, BIM has been considered the main step to digital construction and has been integrated with various construction processes such as facility elevations, prefabricated construction projects, and project management activities [16]. However, one of the fundamental functions of BIM is efficient progress control of construction activities, which could not be achieved without effective progress monitoring [17].

The construction industry is persuaded toward the adoption of automated progress monitoring/detection/recognition/tracking technologies; however, hesitation remains among stakeholders due to technological and operational costs because of the unavailability of required knowledge and information regarding these technologies [18]. Automated progress assessment using digital technologies is an emerging area among researchers; however, substantial research has been accomplished on its practical applications in construction projects. Most of the studies have identified the implementation parameters and conditions focused on individual or specific monitoring technology for its execution methodology frameworks integrated with advanced techniques. Wang et al. [17] proposed an advanced technological BIM integrated framework based on computer-vision-based methods. The framework was only focused on progress measurement of precast walls during execution via data collected during surveillance video recording. Harichandran et al. [19] machine-learning-based hierarchical framework to enhance the operational accuracy of the identification of an "automated construction system (ACS)". In another study, Arif & Khan [20] introduced a framework for real-time tracking of construction activities. The framework was designed for small to medium-sized construction firms and integrated the total station survey data to BIM via cloud computing.

By contrast, few studies have been executed contemplating the overall general process of automated progress measurement using monitoring technologies, in which critical parameters and limitations have been highlighted for the effective implementation of procedures. Alizadehsalehi & Yitmen [21] developed an automated monitoring model, highlighting the field parameters focusing on BIM integrated data-acquisition technologies for construction projects. The model illustrated the managerial propositions by concentrating on the benefits, constraints, and procedures of BIM integrated technologies. In the same way, Alizadehsalehi & Yitmen [18] examined the effects of automated progress assessment practices on the key project performance indicators, i.e., time, quality, and cost. The study adopted structural equation modeling (SEM), and various construction performance control processes were identified under traditional and digital progress monitoring environments. These aforementioned studies have characterized the performance-based multilevel parameters and significant paradigms of the project, promoting the evolution of the automated construction sector. Thus, Alaloul et al. [22], on the progress monitoring of building construction projects via digitized technologies, emphasized the lack of operational guidelines and working frameworks. The study also accentuated the varying working circumstances for various monitoring technologies and working frameworks to be designed considering the internet of things (IoT) environment.

The discussion above concludes that a need to investigate the parameters and technical characteristics affecting the performance of automated progress monitoring for better understanding and confidence gain of construction industry stakeholders does exist. The hesitation of the industry practitioners has been felt toward technological solutions, which may be due to the unavailability of critical procedural parameters causing a theoretical gap [23, 24]. The researchers have indicated the absence of knowledge management standards, specifications, and reference frameworks as the main reasons for the reluctance of the construction industry stakeholders toward adopting technologies [25, 26]. The construction industry is moving at a swift pace toward digitalization under the fourth industrial revolution (IR 4.0). To make the dream of digitalized construction environment successful and promote the IR 4.0 environment, motivating industry

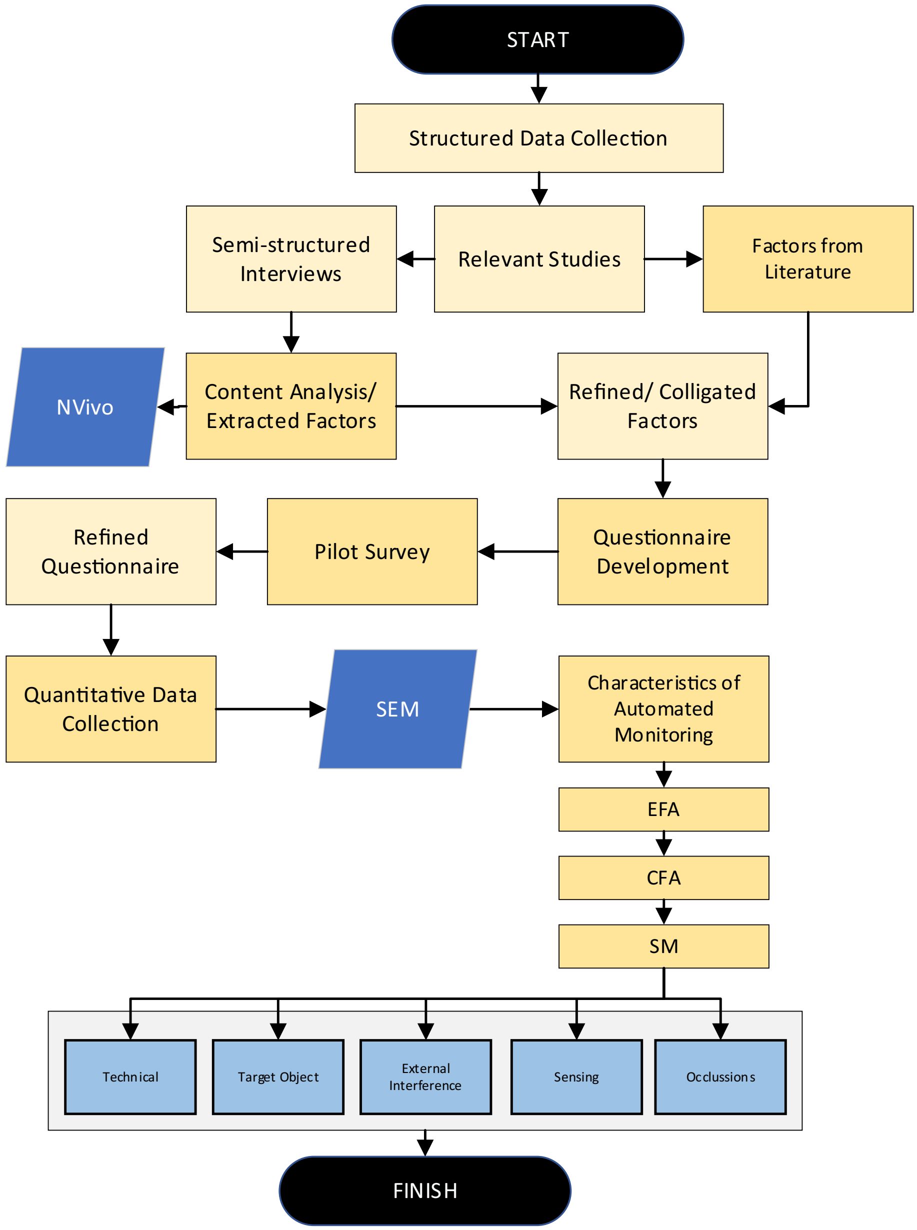


Fig. 1 Study methodology flowchart

stakeholders to adopt intelligent systems for construction processes by providing them clarity to overcome related concerns is needed. This study aims to develop the scientific model by covering theoretical-based technological attributes of the automated monitoring method and developing knowledge management standards for efficacious implementation of automated detection technologies. The SEM technique has been used to highlight efficacious parameters for automated monitoring for each technology and determine a conceptual framework to accomplish the study objective. This study has been centered on the close-range monitoring technologies, which could be continuous or single detection operations, and can be asynchronous (post) or synchronous (real-time). Researchers have generally defined procedures or operations falling under the distance of 100–200 m as close-range processes [27, 28]. This study has established the reference model considering close-range monitoring technologies for efficacious implementation on construction sites during progress assessment activities, which would provide a quick operational understanding to construction industry professionals and stakeholders to gain confidence in applying smart systems. This study's strength is its capability to stimulate this knowledge domain toward the development of the base technological model to improve the performance of construction automated progress monitoring technologies for effectual outcomes.

2 Methodology

The methodology is divided into various phases to achieve this study objective, and each phase is carefully designed for effective execution and outcomes. In the commencement phase, the relevant literature was collected via structured data searching to identify the parameters affecting the performance of automated progress-monitoring technologies. The qualitative and pilot surveys were performed with industry professionals and academicians, leading to the development of questionnaire-based survey for quantitative data collection. The collected data were analyzed via SEM analyses, and conceptual framework was developed to employ automated progress monitoring technologies efficiently. Figure 1 illustrates the flowchart of the methodology adopted in this study.

2.1 Structured Literature Collection

In the commencement phase, systematic data collection was performed for previous studies on the construction progress monitoring via digital technologies. The search scope was limited to "close-range data acquisition-detection techniques". Data collection from past literature is vital, as it leads to the selection of scientific studies and outcomes that establish the conclusion for any review [29]. Therefore, four databases, i.e., American Society of Civil Engineers (ASCE), Science Direct, Scopus, Web of Science (WoS), and a search engine, i.e., Google Scholar, were chosen for literature collection for the time period from 2010 to 2021. The literature search was performed using various combinations of keywords designed for each database. The keywords combination was set broadly for collecting maximum articles under automated construction progress monitoring and filtered based on study scope. Table 1 shows a summary of data collection outcomes and applied parameters.

A total of 1560 articles were collected using the designed keyword combinations, and out of them, 205 articles were found relevant under the defined scope, comprising journals and conference articles covering the review and technical studies. A detailed review was conducted on the collected 205 research articles to identify effective domains, technologies, and parameters adopted for the close-range monitoring practices in the construction projects. Studies acknowledged nine progress monitoring technologies falling under the category of close range, i.e., videogrammetry, photogrammetry, laser scanner, kinect sensors, UWB, RFID, AR, swarm nodes, and infrared thermography [22]. Table 2 illustrates the outcome summary of the evaluated characteristics/parameters from the selected literature in reference to close-range digital

Table 1 Summary of data collection outcomes and applied parameters

Database/search engine	Keywords combination	Total collected studies	Relevant studies
WoS	"TS = (automat* AND (construction OR project OR progress) AND (monitor* OR updat* OR track* OR detect* OR recogn*))"	624	56
Scopus	"TITLE-ABS-KEY (automat* AND (construction OR project OR progress) AND (monitor* OR updat* OR track* OR detect* OR recogn*))"	472	66
ASCE	"((automated OR automation) project monitoring) AND (construction project updating) AND (construction progress tracking) AND (construction progress detection) AND (construction progress recognition)"	150	30
Science direct	"(automated OR automation) AND (construction OR project OR progress) AND (monitor OR updat OR track OR detect)"	231	43
Google scholar	"automated construction project monitoring OR construction project updating OR construction progress tracking OR construction progress detection OR construction progress recognition"	83	10
Total		1560	205

Table 2 Evaluated characteristics/parameters from the literature review

Categories	Subcategories	Parameters	**Sources**
3D scanner	Density point cloud	Higher number of passes	[30, 31,32, 33]
		Presence of false-negative point clouds	
	Site occlusions	Blockage by static elements	[34, 35, 36, 37]
		Blockage by dynamic objects	
	Specifications	Accuracy varies with model	[38, 39, 40, 36, 7]
		Range of laser scanner	
		Scanning distance to the object	
		Angular resolution	
		Incident angle	
	Environment	Weather condition	[31, 41, 32, 42, 37]
		Time of shooting	
		Reflection of laser from glass and surfaces	
	BIM	Level of detail in the planned model (LOD 300, LOD 400, LOD 500)	[22]
Digital imaging (camera, smartphone, CCTV, drone, etc.)	Construction site image	Higher number of images give good results	[43, 44, 45, 46]
		Higher resolution of image	
	Environment	Time of shooting	[47, 48, 49, 11, 50]
		Conditions of shooting	
		Objects with same color and shape affect results	
		Extreme lightning condition is not recommended	
	Site occlusions	Blockage by static elements	[51, 52, 10, 35]
		Blockage by dynamic objects	
	BIM	Level of detail in the planned model (LOD 300, LOD 400, LOD 500)	[22]
	Drone	Rotational and angular movement affects results	[53, 54, 55, 13, 56]
		Drone distance from the object	
		High angular velocity affects results	
		Results are dependent on drones' specifications	
Tracker devices (sensing technology and tags)	Reading device	Accuracy is affected in several tags	[57, 58, 59, 60, 61]
		Detection range	
	RFID	Results inaccuracy in the presence of metal and liquids	
AR/VR	Technology	Type of technology	[62, 63, 64, 65]
	BIM	Level of detail in the planned model (LOD 300, LOD 400, LOD 500)	[22]
Digital video (camera, smartphone, CCTV, drone, etc.)	Video quality	Number of frames enhances results	[66, 67, 68, 69]
	Occlusions	Blockage by static elements	[45, 70, 71, 72]
		Blockage by dynamic objects	
	Drone	Rotational and angular movement affects the video quality	[73, 53, 74, 18]
		Drone distance from the object	

Table 2 (continued)

Categories	Subcategories	Parameters	**Sources**
		High angular velocity will reduce accuracy	
		Features vary with model specifications	
	BIM	Level of detail in the planned model (LOD 300, LOD 400, LOD 500)	[73, 53, 74, 18]
	Data capturing	Data capture distance	[66, 67, 68, 69]

technologies for effective implementation progress monitoring process. Thus, five major data collection domains were identified for automated progress monitoring, i.e., (1) digital site images via camera, smartphone, CCTV, or drone, (2) 3D scanner, (3) digital site video via camera, smartphone, CCTV, or drone, (4) tracker devices, and (5) AR/VR, with 40 overall parameters.

2.2 Qualitative Analyses

A qualitative questionnaire was prepared based on the collected information consisting of general queries on digital monitoring technologies and identified data collection domains. The questionnaire comprised five sections, with the first section covering general queries, and the remaining sections consisted of discussion on digital imaging techniques (infrared thermography, and photogrammetry), 3D scanner techniques (kinect sensor, and laser scanning), digital video techniques (videogrammetry), tracking and sensing techniques (RFID, UWB, and swarm nodes), and AR)/VR. For semi-structured interviews, various studies indicate a varying number for a minimum sample size. The sample size selection seems to be a simple procedure. By contrast, this number is a base that supports the inquiry, as qualitative data collection is goal-directed to obtain enriched information [75]. Kremeike et al. [76] recommended a sample size of 10–20 as suitable for interviews, which has also been endorsed by Konstantina Vasileiou et al. [75]. Dworkin [77] highlighted that the vast number of books, book chapters, and research articles indicate minimum interviews with between five to 50 professionals/researchers. Therefore, keeping the minimum suggested number in preview, the semi-structured interviews were performed with 15 academicians and industry professionals. However, due to COVID-19 restrictions, meetings were conducted online via conference interviews. Based on the response of interviewees, the category VR/AR was eliminated from the derived framework. It was suggested that in the construction sector, VR is mainly adopted for site training and design platforms [13, 78]. By comparison, AR outcome is more reliant on the hardware type of the equipment. In the construction progress-monitoring processes, AR comprised superimposed models integrated with the outcomes by imaging techniques. Hence, AR is a virtual phenomenon in real-world scenarios [64]. The collected data was analyzed through qualitative data analysis software, i.e., NVivo. Content analysis was adopted to characterize the substantial words from the interviewees. NVivo coding was used to identify the significant words from the semi-structured interview scripts. Figures 2(a), (b), (c), (d), and (e) show the obtained models from the content of the semi-structured interviews extracted by NVivo.

Four primary categories and related subcategories were established in the content analysis. The primary categories were “Tracking & Sensing”, “Digital Video”, “Digital Images”, and “3D Scanner”, where eight codes were extracted for “3D Scanner”, ten for “Digital Images”, seven for “Digital Video”, and five for “Tracking & Sensing”. A total of 30 codes/parameters were extracted via content analysis using NVivo. The final framework was developed by colligating the outcomes from the literature review and qualitative analysis, leading to a detailed questionnaire-based survey for quantitative data collection. The effective parameters were then modified and refined to 49 parameters under four prime categories, which comprise the outcomes from literature and semi-structured interviews.

2.3 Quantitative Analyses

Based on the outcomes of the qualitative part, a 49-item-based questionnaire was developed for which a pilot survey was conducted. However, the literature establishes differing guidelines concerning the pilot survey’s minimum sample size, i.e., 10 [79], 12 [79], or 10% of the project sample size [80]. Therefore, the pilot survey was performed with 20 academicians and construction industry experts. Detailed responses were received, and the questionnaire was refined and improved to 36 items under four prime categories. Table 3 illustrates the complete framework with 49 parameters highlighting categories, subcategories, related parameters, and performed actions (maintained or modified or deleted) based on pilot survey responses for the improvement in the final framework.

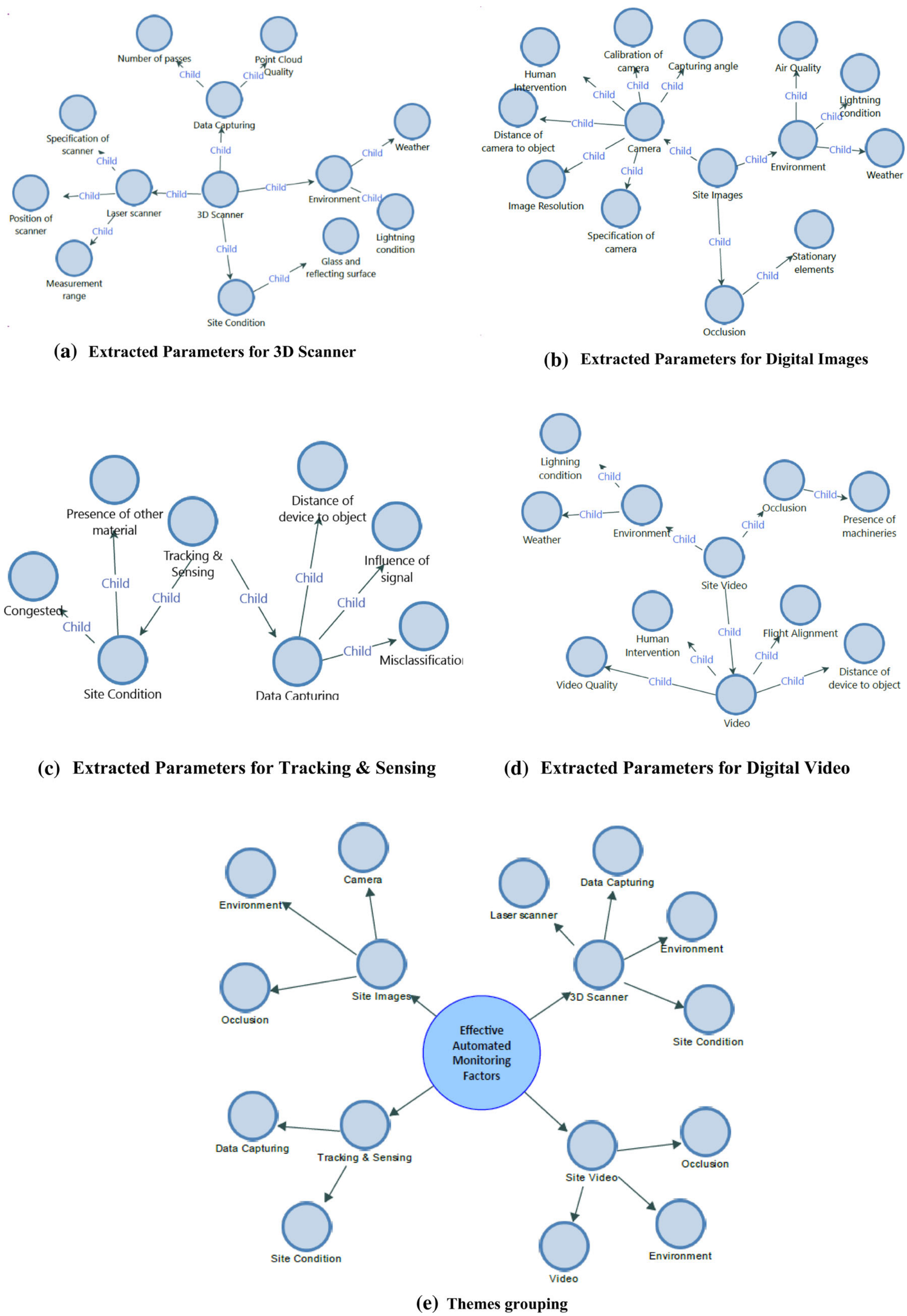


Fig. 2 Content analysis (**a**): Extracted parameters for 3D scanner, (**b**): Extracted parameters for digital images, (**c**): Extracted parameters for tracking & sensing, (**d**): Extracted parameters for digital video, (**e**): Themes grouping

Table 3 Colligated framework (49 parameters)

Categories	Subcategories	Codes/parameters	Remarks
3D scanner (kinect sensor, and laser scanning)	Site condition	Glass and reflecting surface	Modified
	Point cloud density	Number of passes	Deleted
		Presence of false-negative	Deleted
	Occlusion	Dynamic elements	Maintained
		Stationary elements	Maintained
	Laser scanner	Accuracy	Deleted
		Angular resolution	Deleted
		Measurement range	Maintained
		Position of scanner	Maintained
		Specification of scanner	Maintained
	Environment	Lightning condition	Modified
		Weather	Maintained
	Data capturing	Number of scan points	Maintained
		Point cloud quality	Maintained
	BIM	Level of detail (LOD 300, LOD 400, LOD 500)	Deleted
Digital images (infrared thermography, and photogrammetry)	Digital camera/CCTV/drone/smart phone	Calibration of camera	Maintained
		Number of images	Maintained
		Image resolution	Maintained
		Specification of camera	Maintained
		Distance of camera to object	Maintained
		Capturing angle	Maintained
		Human intervention	Maintained
	Environment	Air quality	Maintained
		Similarity of object	Deleted
		Shooting time	Deleted
		Weather	Maintained
		Lightning condition (photogrammetry)	Modified
	Occlusion	Stationary elements	Maintained
		Dynamic elements	Maintained
	BIM	Level of detail (LOD 300, LOD 400, LOD 500)	Deleted
Digital video (videogrammetry)	Data capturing	Rotational and angular movement (drone)	Deleted
		Data capturing distance	Deleted
	Video quality	Number of frames (frame per second)	Deleted
	Occlusion	Dynamic elements	Deleted
		Stationary elements	Maintained
	Environment	Weather	Maintained
		Lightning condition	Modified
	Smart phone/video camera/drone	Specification	Maintained
		Video quality	Maintained

Table 3 (continued)

Categories	Subcategories	Codes/parameters	Remarks
		Shooting location	Maintained
		Flight alignment (drone)	Modified
		Human intervention	Maintained
	BIM	Level of detail (LOD 300, LOD 400, LOD 500)	Deleted
Tracking & sensing (RFID/UWB/swarm nodes)	Data capturing	Presence of several tags	Maintained
		Misclassification of material	Modified
		Influence of signal	Maintained
		Distance of device to object	Maintained
	Site condition	Presence of other material	Modified
		Congested site	Maintained

The questionnaire was finalized on 36 parameters. To investigate the opinion of the industry on efficacious parameters of close-range automated progress detection technologies for construction projects, the Likert scale methodology was adopted. The Likert scale was set to the scale of 1–5, where 1 = "Strongly Disagree", 2 = "Disagree", 3 = "Neutral", 4 = "Agree", and 5 = "Strongly Agree". The questionnaire distribution was made following two varying strategies. To collect the responses, the questionnaires were forwarded to Malaysian construction industry professionals and contractor companies. As per the record of the "Construction Industry Development Board (CIDB) Malaysia", the total number of registered contractors is 95,997 [81]. In academia, the opinion was collected from around the globe, i.e., the questionnaires were emailed to academicians in the United States of America (USA), Malaysia, India, Hong Kong, the Kingdom of Saudi Arabia (KSA), Pakistan, United Kingdom (UK), and Australia. The sample size for this study was calculated by using Israel [82], with 99 as the minimum number of respondents. However, the distribution was made to more than 700 construction industry and academia-based individuals.

Based on the collected responses, the SEM was performed. SEM was introduced in the 1980s, and because it is considered a versatile multivariate statistical technique, a quasi-routine, for testing hypotheses about relations among latent variables and observed [83]. SEM comprises two models, the first model, which is known as the measurement model, performs confirmatory factor analysis (CFA), which correlates the constructs by measuring variables to latent factors by testing their validity and reliability as per defined standards to refine the model. The second model, which is known as a structural model, evaluates the relationships between the latent factors by determining variances (explained and unexplained), testing the hypotheses, and refining the model accordingly. It replaces the constructs' correlation to the anticipated causal relations in the conceptual model and tests the hypothesis by modifying the model until it satisfies the criteria [84]. SEM can be performed either on the theory-based conceptual frameworks or frameworks developed based on exploratory factor analysis (EFA). EFA investigates the appropriateness of the proposed combination of variables or attributes and explores the probable underlying factor structure of a group of observed variables without imposing a pre-determined structure on the outcome [85]. A conceptual framework was developed in this study for the evaluation by SEM, which was designed by performing EFA on the identified automated monitoring parameters to develop a technical characteristics-based framework.

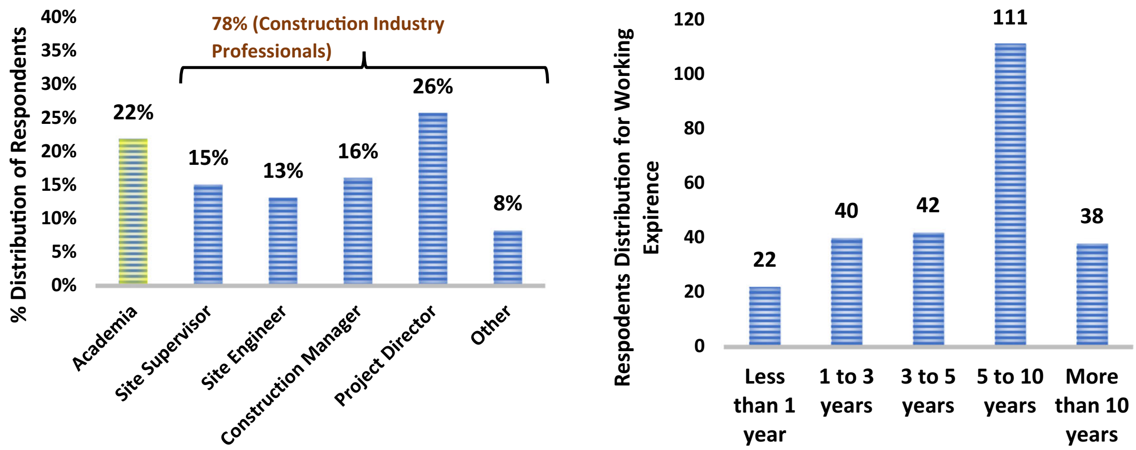
3 Results and Analyses

3.1 Data Collection and Reliability Test

To collect the data from the construction industry professionals and academia, more than 700 questionnaires were sent via email, and 253 responses were received. Figures 3(a) and (b) represent the demographic profile summary of respondents.

It can be observed that 78% (197) of the responses were collected from the professionals and practitioners of the construction industry, wherein 22% (56) of the responses were from academia. Good feedback was collected from experienced individuals, as 15% (38) of respondents were above ten years of experience, and 44% (111) of the respondents had work experience of more than five years. Only 22% (55) of respondents were with experience of less than one year on the job.

The collected responses were then tested to analyze the internal consistency of the data by using Cronbach's alpha. The Cronbach's alpha is "an evaluation of internal reliability or consistency between a number of objects, ratings, or



(a) Percentage distribution against job title **(b) Distribution against work experience**

Fig. 3 Demographic profile summary (**a**): Percentage distribution against job title, (**b**): Distribution against work experience

Table 4 Cronbach's alpha summary

Categories	Subcategories	Number of parameters	Cronbach's alpha
Tracking & sensing	2	6	0.88
Digital images	3	12	0.93
Digital video	3	8	0.91
3D scanner	5	10	0.92
Overall cronbach's alpha	13	36	0.92

measurements". It is a simple statistical tool to calculate and check the credibility of collected feedback or survey responses [86]. In this case, 253 responses data were tested by applying Cronbach's alpha to each category separately and the whole collected data. The attained Cronbach's alpha values (α) of each section, except for "Tracking & Sensing" (0.88), were above 0.90. As a rule of thumb, $\alpha \geq 0.9$ is deemed excellent, while $\alpha \geq 0.7$ is believed reliable. Most researchers have considered $\alpha \leq 0.55$ as unsatisfactory [87, 88]. Table 4 illustrates the summary of the reliability test for 253 response data.

3.2 Development of Conceptual Framework

SEM is a popular statistical analysis technique in quantitative social research. SEM success can be attributed to the simplicity of the underlying scientific model, as well as the ability to solve critical substantive problems. SEM has three significant advantages over traditional multivariate techniques: (1) precise assessment of measurement error; (2) testing of model till structure can be enacted and assessed as to fit of the data; and (3) estimation of (unobserved) latent variables with observed variables. Most multivariate methods inadvertently disregard measurement errors by not directly predicting them, while SEM models approximate these error variance parameters for both dependent and independent variables [89]. SEM evaluation has been performed in this study to achieve a better refined automated monitoring framework. The developed framework explains the general parameters for effective implementation of the digital monitoring process for construction projects.

The conceptual framework has been designed by performing EFA on the refined 36 parameters to develop a characteristics-based framework for effective automated monitoring implementation. This exercise aimed to sort technological parameters based on their characteristics, affecting the implementation of automated monitoring. The EFA is known as a data reduction technique and helps in identifying the framework from the collected data. In this study, the principal axis factor methodology and the varimax rotation method have been adopted, identifying automated monitoring effective parameters and better interpretability of factor loadings. In reference to the sample size, the items with a factor loading of less than 0.40 were screened out [90] in the EFA as weak indicators of the construct. Table 5 shows a summary of the extracted EFA model.

In the EFA, few parameters, i.e., P8 (air quality), P9 (weather), V2 (weather), L1 (glass and reflecting surface), and L2 (occlusion-stationary element) were excluded either due to factor loadings of less than 0.4 or due to cross-loading, and this led to the refined conceptual framework. The EFA concluded all parameters under five constructs, i.e., "Technical", "Target Object", "Occlusions", "Sensing",

Table 5 Extracted parameters from EFA

Factors	ID	Technical	Target object	External interference	Sensing	Occlusions
Number of images captured in the site	P2	0.850	–	–	–	–
Image resolution	P3	0.794	–	–	–	–
Calibration (smart phone/CCTV/drone/digital camera)	P1	0.786	–	–	–	–
Specification (CCTV/smart phone/drone/digital camera)	P4	0.705	–	–	–	–
Capturing angle	P6	0.681	–	–	–	–
Distance of device to object	P5	0.656	–	–	–	–
Human intervention	P7	0.550	–	–	–	–
Lightning condition	P10	0.539	–	–	–	–
Weather	L8	–	0.753	–	–	–
Specification (laser scanner)	L6	–	0.735	–	–	–
Position of scanner	L5	–	0.732	–	–	–
Number of scan points	L9	–	0.724	–	–	–
Point cloud density	L10	–	0.707	–	–	–
Measurement range	L4	–	0.613	–	–	–
Lightning condition	L7	–	0.586	–	–	–
Shooting location	V6	–	–	0.830	–	–
Video quality	V5	–	–	0.776	–	–
Human intervention	V7	–	–	0.739	–	–
Specification (video camera/drone/smart phone)	V4	–	–	0.735	–	–
Lightning condition	V3	–	–	0.699	–	–
Flight alignment (drone)	V8	–	–	0.694	–	–
Influence of signal	T5	–	–	–	0.755	–
Misclassification of material	T4	–	–	–	0.753	–
Presence of several tags/barcodes	T3	–	–	–	0.728	–
Congested site	T2	–	–	–	0.715	–
Presence of other material	T1	–	–	–	0.621	–
Distance of reader to object	T6	–	–	–	0.612	–
Occlusion–dynamic element (photogrammetry)	P12	–	–	–	–	0.819
Occlusion–dynamic element (laser scanning)	L3	–	–	–	–	0.762
Occlusion–stationary element (videogrammetry)	V1	–	–	–	–	0.751
Occlusion–stationary element (photogrammetry)	P11	–	–	–	–	0.736

and “External Interference”. Based on this collected data, the measurement model was developed to perform CFA to evaluate the reliability and validity of the conceptual framework. The observed variables with loadings of less than 0.6 were deleted [91] in CFA. Figure 4 illustrates the final fit of the measurement model for technical characteristics/parameters for the efficacious application of automated monitoring.

The final refined parameters/variables have been categorized under five constructs, i.e., “Target Object”, “Technical”, “Sensing”, “Occlusions”, and “External Interference”. CFA was performed on the finalized framework, while P3 (image resolution), P7 (human intervention), P10 (lightning condition), V3 (lightning condition), and T6 (distance of reader to object) were deleted either due to containing factor loadings

Fig. 4 Measurement model based on effective parameters for automated monitoring

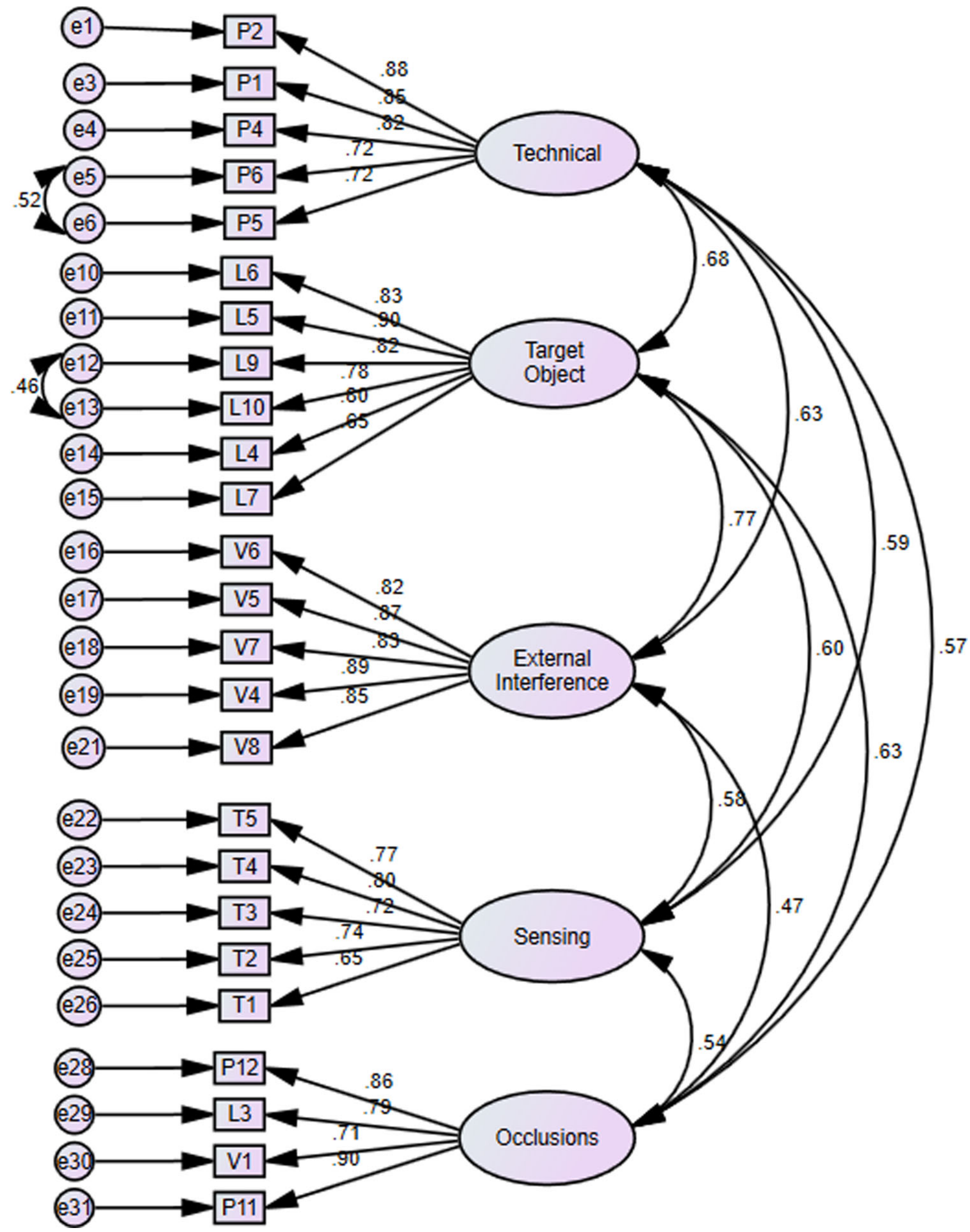


Table 6 Reliability and validity of the parameters

Constructs	Cronbach's Alpha (α > 0.6)	CR (CR ≥ 0.6)	AVE (AVE ≥ 0.5)	Sensing	Technical	Target Object	External Interference	Occlusions
Sensing	0.85	0.855	0.543	0.737				
Technical	0.90	0.899	0.642	0.591	0.801			
Target Object	0.90	0.914	0.640	0.599	0.678	0.800		
External Interference	0.93	0.931	0.729	0.583	0.627	0.770	0.854	
Occlusions	0.80	0.888	0.666	0.544	0.575	0.629	0.473	0.816

Table 7 GOF indices for measurement model

Index	Acceptance criteria	Attained values
Chisq	$p > 0.05$, $p > 0.01$	586.566
RMSEA	< 0.08	0.07
GFI	> 0.90, > 0.80	0.81
CFI	> 0.90	0.91
TLI	> 0.90	0.91
Chisq/df	< 2,3	2.2

of less than 0.6 or for variables showing large covariance values. In the model, for the improvement, error correlations have been established for the variables P5-P6 (distance of device to object-capturing angle), and L9-L10 (number of scan points-point cloud density); however, correlated variables are unique parameters and have no similarity. Table 6 shows the reliability and validity tests for the measurement model.

The goodness of fit (GOF) model fit is shown in Table 7. Based on the model fit of the measurement model and structural model (SM) was developed, as shown in Fig. 5, which was assessed for model fit by the following GOF indices, as shown in Table 8.

The attained SM comprised five primary constructs with 25 general parameters. Five parameters have been refined under "Technical" construct, six under "Target Object", five under "Sensing", four under "Occlusions", and five under "External Interference". GOF indices have been assessed for both CFA and SM, which validates the model fit.

4 Discussion

This study designed the reference model for automated construction progress monitoring via close-range data acquisition and detection technologies by following a strategy based on a structured literature review, semi-structured interviews, and questionnaire surveys, which led to the development of knowledge-based standards. Furthermore, the critical parameters for effective implementation of the automated construction monitoring process have been identified and refined by executing SEM. This study's theme was to design a conceptual framework highlighting the general technical parameters supporting progress monitoring operations. The conceptual framework has been attained by analyzing and refining 25 parameters of SM under five constructs to 21 general characteristics under five constructs, as few parameters were conceptually common but were varied based on technologies. Figure 6 represents the framework highlighting general parameters for the efficacious application of the automated construction progress monitoring process via close-range digital technologies. The framework has been generalized for its parameters, irrespective of technology. Repeated parameters under the same construct or other construct have been merged or removed to make it more practicable.

Five parameters have been catered under the "Technical" construct, and this group basically defines the overall technical aspects related to data capturing gadgets, which may affect the monitoring outcome. A good calibrated and high-specification device may capture enriched data. Likewise, the quality of data can be compromised depending on the distance of the device from the targeted object, its capturing angle, and fewer images/scans/passes. Five parameters have been refined under "Sensing", highlighting the aspects that may affect the results. The sensing and tracking gadgets' outcomes may deviate in the presence of other materials (metals and liquids), congested site conditions, and the presence of several tags, which may lead to the misclassification of materials. The detection accuracy of tracking and sensing devices also depends on the signal's strength. The conceptual framework defines only two parameters under "Occlusions", as irrespective of any monitoring technology, the obstructions have been observed either due to stationary or moving objects. However, the construct "Target Object" reflects five parameters, which define general characteristics linked with the monitoring operation and outcome of the desired structure. The range of the device to the object, its position, and lighting directly affects the outcome of data capturing technologies. It affects the quality of attained data, such as data density. Lighting has no impact on "Tracking & Sensing" technologies; it is more related to imaging, video, and scanning devices. However, rapid light fluctuation may interfere with sensing tags. The last construct, "External Interference," highlights the parameters such as the location of the activity, flight alignment in the case of drones, and human intervention during digital monitoring, which may adversely affect the quality of data collection.

The structured literature review revealed that not many studies have been primely focused on identifying technological parameters in the automated monitoring domain. However, executed studies have focused on the effect of automated monitoring technologies on construction processes considering key performance indicators or BIM following SEM, such as studies by Alizadehsalehi & Yitmen [18] (already discussed in the Introduction section), and Alizadehsalehi & Yitmen [92], which proposed SEM-based model for BIM-based field data capturing technologies. However, the latter study only focuses on the effects of automated project progress monitoring via field data capturing technologies only considering BIM workflows. Many studies have explained the relationship between technologies against operational variables. Kopsida et al. [2] compared random construction progress monitoring technologies and

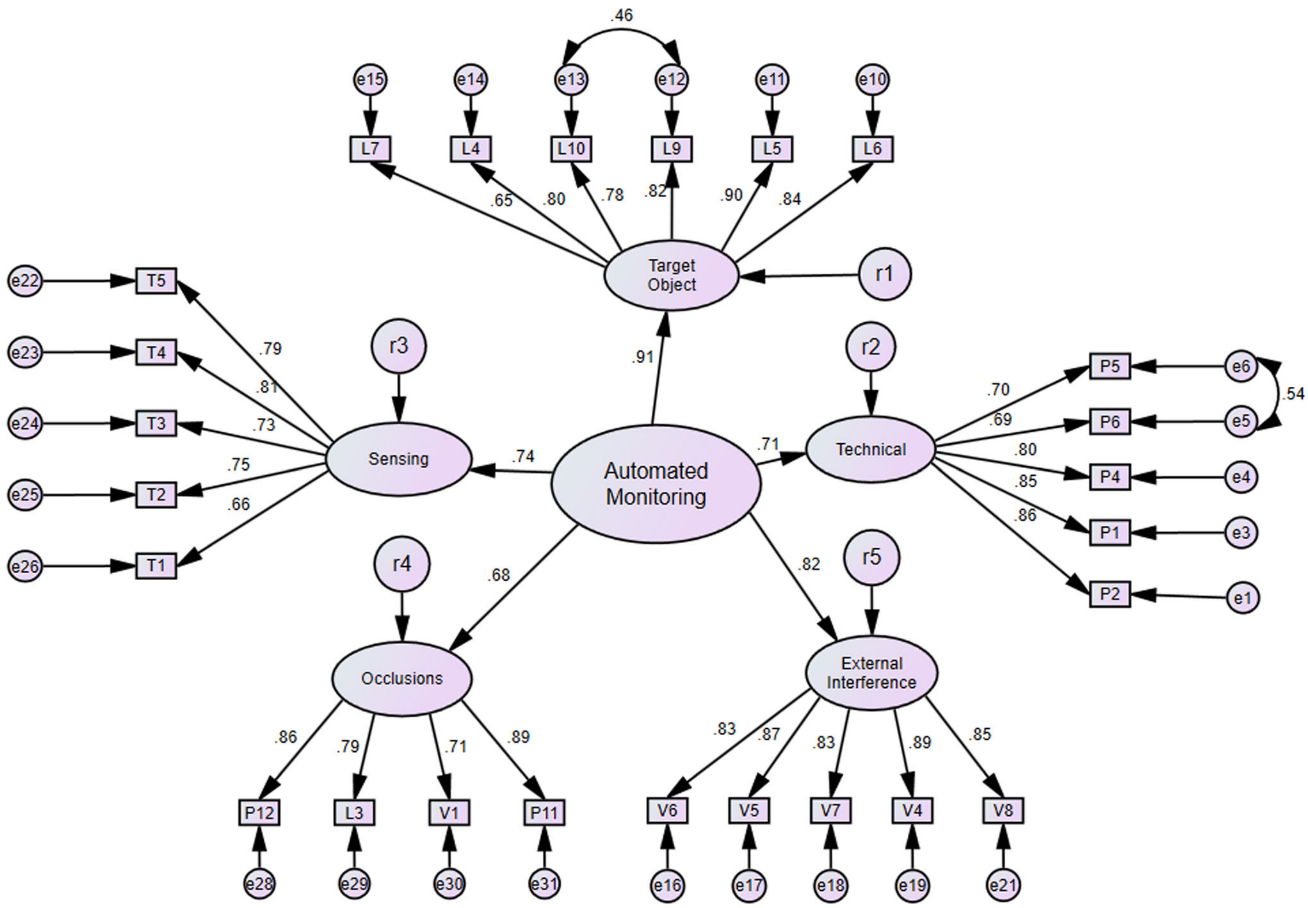


Fig. 5 Structural model based on effective parameters for automated monitoring

assessed them in terms of general parameters such as accuracy, required preparation, level of automation, time efficiency, utility, training requirements, mobility, and cost. Pour Rahimian et al. [13] compared imaging techniques, geospatial techniques, and VR/AR techniques for their advantages and limitations. Moreover, it was also revealed from the structured literature review that the majority of studies highlight the factors affecting the outcomes of overall monitoring operation. However, such studies are technology-specific, and associated factors may differ among studies, such as Mahami et al.[93], highlighted the impacts of imaging techniques, and Alex Braun & Tuttas [94], focused on the scanning technique. Moreover, Arif & Khan [20] analyzed the effect of automated progress monitoring in comparison with traditional methods in the environment of the Pakistani construction industry. An economical and real-time tracking framework was suggested for monitoring construction activities. However, the study utilized advanced tracking methodology, i.e., Survey-Cloud-BIM integration via the total station, cloud computing, Dynamo programming, and BIM. The framework was designed to gather construction progress data-activity-wise.

Compared with the aforementioned models, this general characteristic-based automated monitoring model highlights various aspects that can impact the effectiveness of the automated monitoring process. The overall theme of this model is to illustrate the general understanding of the criteria for the efficacious application of automated monitoring processes irrespective of implemented technology. This model offers a general guideline to stakeholders for any close-range monitoring technology and its implementation. Researchers have assessed the outcomes of digital monitoring technologies for the effectiveness of monitoring operations either by comparing performance or ranking related factors by adopting the relative importance index (RII) technique, such as studies performed by Alizadehsalehi & Yitmen [21] and Álvares & Costa [95]. Likewise, Hannan Qureshi et al. [96] highlighted the technology-related factors and a simple framework based on RII. Therefore, in comparison with the aforementioned studies, this conceptual framework has been devised via performing mathematical modeling technique, i.e., SEM, which underlines the precise variables and parameters related to automated progress monitoring process, to confidence gain

Table 8 GOF indices for structural model

Index	Acceptance criteria	Attained values
Chisq	$p > 0.05$, $p > 0.01$	608.14
RMSEA	< 0.08	0.07
GFI	> 0.90, > 0.80	0.81
CFI	> 0.90	0.91
TLI	> 0.90	0.91
Chisq/df	< 2,3	2.2

on its application, basics operational guidelines, and to educate construction industry stakeholders. The model is unique because it focuses on the general parameters that affect the performance of the digital monitoring operation and is easily understandable by the practitioners.

5 Conclusion

This study aimed to identify and highlight basic parameters that affect the performance of automated technology-based progress monitoring in construction projects. The study followed a structured literature review strategy and selected relevant studies. The performance-based technological parameters were extracted, and 49 parameters were finalized based on literature and semi-structured interviews. These automated monitoring technological parameters were refined to 36 items based on the feedback in pilot surveys. The questionnaire-based feedback was collected by the industry professionals and academicians on refined parameters. An SEM-based statistical analysis approach was adopted based on the collected responses, which directly focused on the automated monitoring process implementation parameters. A refined model was achieved following SEM analyses, highlighting the characteristics that provide the foundation for the efficient operation of close-range automated monitoring technologies. The developed conceptual framework reflects the 21 general parameters impacting the application of the automated monitoring process, which has been developed by performing EFA and CFA. These parameters reflect the main characteristics affecting automated monitoring implementation and are grouped under the related constructs, i.e., "Target Object", "Technical", "Occlusions", "External Interference", and "Sensing". This model illustrates the aspects that support the effective implementation of automated monitoring

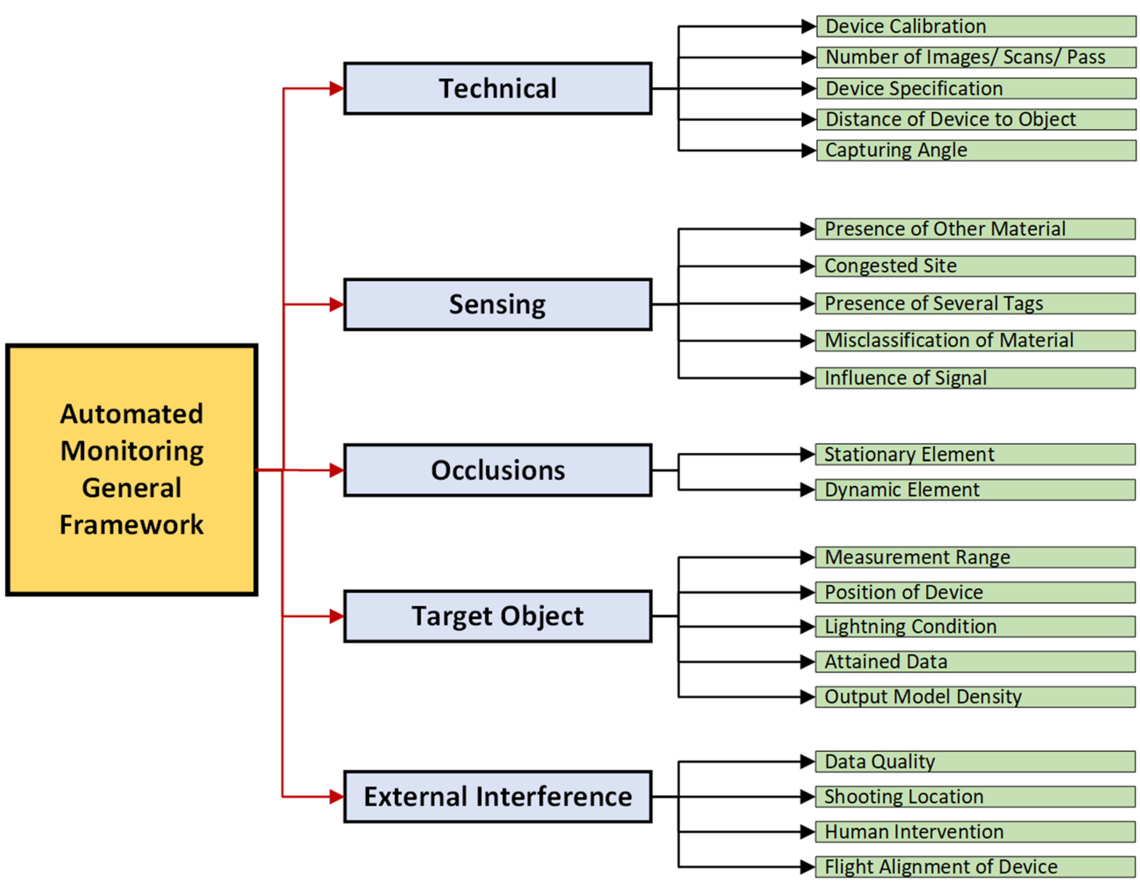


Fig. 6 General characteristics based conceptual framework for automated monitoring process

processes and would help stakeholders in understanding the general parameters. The structured literature review performed in this study highlighted that not many studies could be found focusing on the automated progress monitoring implementation of basic frameworks and guidelines. Therefore, this study intended to deliver a knowledge framework to consummate the information gap, which fuels the hesitation of construction industry stakeholders towards technologies. The achieved model will encourage the construction industry practitioners to the adoption of monitoring technologies, supporting the IR 4.0 environment and being cost-beneficial in the long run.

The model has been designed considering the main parameters affecting automated monitoring performance. However, for future considerations, SM can be assessed for the impacts of automated monitoring on the project performance control or key performance indicators (cost, time, and quality), related project's primary or secondary processes (safety management, project planning, supply chain management, and so on), and external implications (CO2 emission). Moreover, these models can be extended to spatial monitoring technologies for building and highway projects for an overall preview.

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Data Availability Statement All data, models, and code generated or used during this study appear in the submitted article.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could appear to influence the work reported in this paper.

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