Developments in the Built Environment 12 (2022) 100087

Contents lists available at ScienceDirect

Developments in the Built Environment

journal homepage: www.sciencedirect.com/journal/developments-in-the-built-environment

Digital technology for quality management in construction: A review and future research directions

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ARTICLE INFO

Keywords:
Quality management
Digital technology
Quality defects
Quality culture
Behavioral quality

ABSTRACT

Significant developments in digital technologies can potentially provide managers and engineers with the ability to improve the quality of the construction industry. Acknowledging the current and future use of digital technologies in construction quality management (CQM), we address the following research question: *What developments in digital technologies can be used to improve quality in the construction industry*? In addressing this research question, a systematic review approach is used to examine the studies that have been used for the management of quality in the construction industry. This review indicates that there is a need for digital technology-based quality management to be: (1) enhance defect management for concealed work, (2) enhance pre-construction defects prevention as well as post-completion product function testing, and (3) research on construction compliance inspection as a direction. We suggest that future research focus on quality culture development, advanced data analytics, and behavioral quality assessment.

1. Introduction

From design to project delivery, construction quality is the result of joint actions from multiple participants on the premise of safety operation. The construction industry is widely criticized for the low-quality delivery of construction projects, especially in terms of finished products, as well as the processes used during the project design and construction stages (Marasini and Quinnell, 2010). Quality problems and defects such as waterproof roof leakage, wall deformation and cracks, insufficient floor thickness, floor base bulging and cracking, and coating falling off still occur from time to time (Forcada et al., 2016), (Alencastro et al., 2018). In addition, construction accidents are seldomly caused by unqualified construction practitioners. Compared with manufacturing and service industries, new employment rates are declining every year in the construction industry ('The next normal in construction, 2020) due to poor working conditions (Söderberg et al., 2021), low employment stability (Jide et al., 2018), and high occupational risk (Meng et al., 2018).

Digital technologies (e.g., Building Information Modeling, Internet of Things, etc.) have been applied substantially to construction safety (Guo et al., 2021a), cost (Vigneault et al., 2020), and schedule (Chen et al., 2021), while quality management has received less research in this area. The existing quality research focused on applying a single digital technology to specific quality management problems. Numerous previous studies have demonstrated the application of building information modeling (BIM) and construction surface quality inspection. No state-of-the-art review examined the extant research, proposed future research directions, and determined the current limitations of digital technologies in CQM. Such a review is needed to examine the developments and provide an avenue for ensuring that future research has a robust theoretical underpinning.

To this end, this study aims to examine digital technologies applications and identify opportunities and challenges for digital technologies applications in CQM. To understand the digital-based quality management research status, 108 articles related to the topic were collected, and 44 are further analyzed in Section four. In this paper, a brief overview of the leading existing digital technologies applied to quality management is presented in Section two. Sections two and three describe the existing leading digital technologies applied to quality management and the research methodology of this paper. The current research based on digital technologies is the main focus of Section four. The challenges and future research directions of digital technologies in

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https://doi.org/10.1016/j.dibe.2022.100087
Received 26 April 2022; Received in revised form 16 August 2022; Accepted 16 August 2022
Available online 19 August 2022
2666-1659/

CQM are presented in Sections five and six, respectively. Finally, there is a summary of this paper in Section seven.

2. Major digital technologies applied in CQM

Digital technologies refer to the collection and paradigm of various intelligent and innovative technologies for connectivity, communication, and automation (Ivanov et al., 2019). They have currently been widely used in CQM for information access and manipulation, mainly including BIM, Augmented Reality (AR), Internet of Things (IoT), Computer Vision (CV), and blockchain.

BIM can help eliminate information barriers (Cus-Babic et al., 2014) between architectural design, prefabrication, and construction and help reduce reworks (Khalesi et al., 2020). Research studies on BIM mainly focus on design review (He et al., 2017), construction management (Chen and Luo, 2014) and facility management (Hilal et al., 2019).

AR is a real-time view of the physical real-world environment enhanced by adding virtual information generated by a computer (Carmigniani et al., 2011). AR technology can help facilitate quality management and benefit the project by accelerating onsite training and safety, design and development, and communication with relevant parties (Schiavi et al., 2022).

IoT is essential to simplify the communication between intelligent devices by transmitting or sharing digital data through sensors, actuators, and networks. IoT has been widely used in manufacturing, the service industry, infrastructure management, medical treatment, and national defense (Dai et al., 2019). In the construction industry, IoT is applied in real-time monitoring of construction processes and preventive maintenance (Fang et al., 2020a).

CV can provide enriched information to support and achieve a high-level understanding of objects and events present in a scene through the analysis of digital images or videos (Guo et al., 2021a). CV has been used for construction activities identification (Seo et al., 2015), site productivity assessment (Luo et al., 2018), detection and visualization of dynamic workspaces (Luo et al., 2019), and real-time structural health (Dong and Catbas, 2021). Visual data collected from construction sites are used for site safety (Fang et al., 2020b), abnormal construction activity identification (Lin et al., 2021), and automated postconstruction quality assessment for defects in inspection (Liu et al., 2017).

Blockchain is defined as a distributed ledger technology characterized by decentralized operations across a consensus mechanism network (i.e., peer to peer), where all data are stored as blocks that are immutable once joined and authenticated in a chain (Viriyasitavat et al., 2019). It was originally created for financial transactions, and now it has been gradually applied in the construction industry to enhance quality information management (Sheng et al., 2020).

These digital technologies support quality planning and control through efficient information processing, as shown in Table 1. Besides, Natural Language Processing (NLP), etc. have also been applied in CQM.

Table 1
Research and applications of digital technology in construction.

Technology	Instructions	Research and applications in CQM
BIM (Building Information Model)	Digital representation of physical and functional characteristics, carrying and sharing a large amount of facility information. Achieve visualization, coordination, simulation, optimization, and drawing.	1. Mobile BIM for lean interaction (Koseoglu and Nurtan-Gunes, 2018). 2. Spatiotemporal dynamic 4D planning (Mazars and Francis, 2020). 3. Design review (Hossain et al., 2018). 4. Reducing reworks (Khalesi et al., 2020).
AR (Augmented Reality)	Overlay and integrate site information and virtual reality for continuous interaction and perception.	1. Occupational safety training (Tatic and Tesic, 2017) 2 Multi-user collaborative BIM-AR system (Garbett et al., 2021). 3 BIM data flow architecture with AR/VR (Schiavi et al., 2022).
IoT (Internet of Things)	Ubiquitous computing, Internet protocol, sensing technologies, communication technologies, and embedded devices are merged to form a system where the real and digital worlds meet and are continuously in a symbiotic interaction.	1. Logistic and product lifetime management (Cai et al., 2014). 2. Smart home/building service quality (Hui et al., 2017). 3. Public safety and environmental monitoring (Zhou et al., 2019). 4. Health and well-being (Gyrard et al., 1007).
CV (Computer Vision)	Multidisciplinary synthesis, making the machine learn to "see" and focusing on perception and recognition.	1. Automated defects detection and quality performance assessment (Wei et al., 2021a). 2. Construction activities identification (Seo et al., 2015; Kong et al., 2021; Liu et al., 2022). 3. Site productivity assessment (Luo et al., 2018). 4. Detection of dynamic workspaces (Luo et al., 2019). 5. Abnormal construction activity identification (Lin et al., 2021; Fang et al., 2018). 6. Real-time structural health (Dong and Catbas, 2021). 7. Automated postconstruction quality assessment for defects in inspection (Liu et al., 2017).
Blockchain	A decentralized, open, transparent, secure, and traceable database.	1. Biomedical and health care (Kuo et al., 2017). 2. Supply chain tracking (Bashir et al., 2016).

3. Research methods

This paper first introduces major technologies in CQM, and then collects related articles through strategic searching in Web of Science database. Through bibliometric analysis of keywords, current research status is presented, and future research are discussed. The structure of this review is shown in Fig. 1.

3.1. Related articles selection

As the literature on certain digital technologies in construction quality is not yet abundant, this study selected related articles in two steps. First, articles were initially retrieved through keywords searching on Web of Science of digital technology in CQM。 The keyword search is conducted using the combinations of keywords such as "construction quality + (building information modeling OR BIM OR AR OR IoT OR BC)" published from 2011 to 2022. For example, on blockchain in construction quality, the complete search phrase used in Web of Science was "All in fields: (Blockchain OR BC OR CV) + construction quality." Then, irrelevant articles were excluded through manual abstract reading and screening. One hundred and eight papers from approximately 47 journals related to the topic were identified as an object of this study.

Fig. 2 shows the number of academic articles published from 2011 to 2022 on CQM and digital technology-based CQM. Both topics have shown a periodical fluctuating publication growth since 2011, and related articles have increased sharply in the recent five years due to the accelerated development of multiple digital technologies. The publish trend shows CQM and digital technology-based CQM are highly correlated and implies that digital technology-based CQM takes a certain proportion in CQM research.

Fig. 1. Review structure.

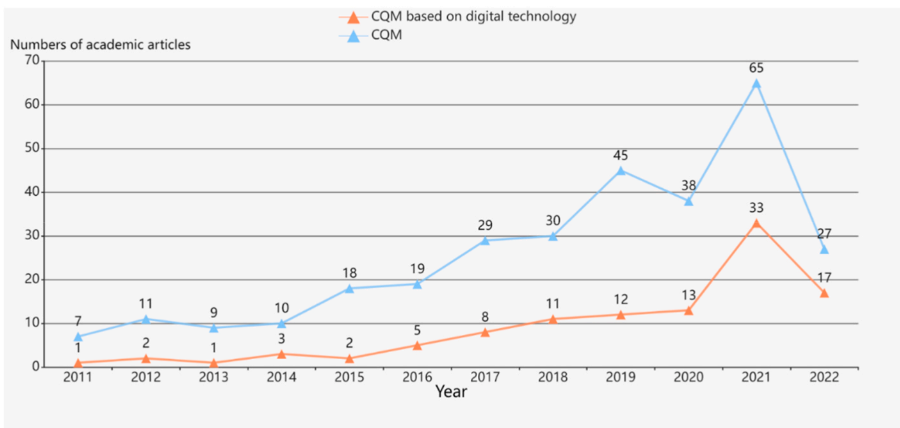

Fig. 2. Articles published from 2011 to 2022 in CQM.

3.2. Bibliometric analysis of digit-based CQM

Based on the collected article, further bibliometric analysis of authors and keywords is conducted with VOSviewer software to visualize the keyword mapping relationship. The keyword network indicates the research theme, the applied digital technology, and its inter-relatedness. The minimum number of occurrences of the set keywords was set to 2, and 56 out of 428 keywords met the threshold. The Keywords network of digit-based CQM is presented in different colors and clustered with research topics, their relationship, and frequency of occurrence. The network illustrates the mapping relationship between technologies and CQM research themes, as shown in Fig. 3.

As shown in Fig. 3, the yellow circular area indicates that BIM is the most widely studied technology and usually incorporates other technologies for quality control, inspection, and compliance check. Other digital technologies such as AR, IoT, CV, and blockchain are scattered in the figure and are less associated with each other.

The top-cited articles on digital technology-based CQM are listed with the author and research theme listed below in Table 2. In this table, quality defects identification and assessment are the most cited and active field in digital technology-based CQM, in which CV plays a critical part for automated quality defects identification. Followed by the compliance check of product and dimensional deviation assessment. The combination of BIM with other technologies also forms a pattern for information manipulation and comparison in CQM.

Through bibliometric analysis, current COM research focuses on the following fields: First, damage and defects identification, including cracks detection based on machine vision and image processing; Second, condition assessment on dimensional deviation analysis and dynamic quality monitoring based on machine vision or image processing; Third,

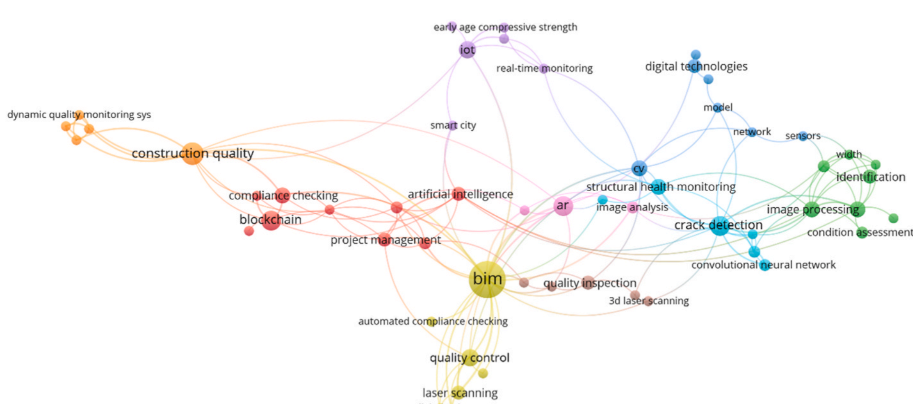

Fig. 3. Digit-based CQM keywords co-occurrence for network visualization.

Table 2
Summary of highly cited literature in digit-based CQM.

No.	Author or Affiliations	Numbers of citations	Theme of CQM	Digital technology
1	Dung and Anh (2019)	309	Quality defects identification and assessment (Dung and Anh, 2019)	CV
2	Zou et al. (2019)	299	Quality defects identification and assessment (Zou et al., 2019)	CV
3	Dorafshan et al. (2018)	214	Quality defects identification and assessment (Dorafshan et al., 2018)	CV
4	Park et al. (2013)	175	Quality defects identification and assessment (Park et al., 2013)	BIM and AR
5	Chen and Luo (2014)	162	Compliance check of product (Chen and Luo, 2014)	BIM
6	Zhang and El-Gohary (2016)	111	Compliance check of product (Zhang and El-Gohary, 2016)	Natural language processing
7	Kim et al. (2015)	108	Quality defects identification and assessment (Kim et al., 2015)	BIM and IoT
8	Kim et al. (2016)	100	Dimensional deviation assessment (Kim et al., 2016)	BIM and IoT
9	Zhou et al. (2017)	79	Dimensional deviation assessment (Zhou et al., 2017)	AR
10	Kwon et al. (2014)	77	Quality defects identification and assessment (Kwon et al., 2014)	BIM and AR
11	Zhong et al. (2012)	71	Compliance check of product (Zhong et al., 2012)	Ontology-based semantic modeling
12	Yang et al. (2020)	71	Quality defects identification and assessment (Yang et al., 2020)	Blockchain
13	Wang et al. (2016)	70	Dimensional deviation assessment (Wang et al., 2016)	IoT
14	Li et al. (2017)	68	Quality defects identification and assessment (Li et al., 2017)	CV
15	Xu et al. (2018)	66	Construction information integration cloud platform (Xu et al., 2018)	IoT

research on compliance checking and quality inspection with blockchain and BIM.

4. Application of digital technology in CQM

The quality inspection process includes quality defect identification, deviation check with design, compliance check with codes and specifications, and test run of functionality. The main challenge is to precisely capture and efficiently analyze construction products for every link of the CQM process. To address this issue, studies on non-contact sensing and defect identification algorithms are widely conducted. Digital technologies that were applied in existing studies could be summarized in four main aspects, as illustrated in Fig. 4.

4.1. Quality defects identification and assessment

Construction quality defects mainly refer to functional deficiency or failure of construction products to meet codes and specifications. Traditionally, quality defects are manually detected during inspection before delivery with visual observation, tape measurement, and the use of a total station. However, construction site operation is labor-intensive and may make work unaccountable (Fan, 2841).

Currently, research in construction quality defects identification mainly focuses on product surface defects, including cracks, spalling, flatness, and deformation (Fan, 2014; Qiu et al., 2018; Zhou et al., 2021; Li et al., 2021).

(1) Cracks

The development of computer vision methods facilitates continuous monitoring and compensates the human judgment inaccuracy. Vision-based technology has been used in structural crack detection, crack measurement, and crack pattern recognition (Liu and Yeoh, 2021). Testing methods like laser, infrared, radiographic, and thermal testing approaches have been used to automate the process of crack detection and measurement (Zou et al., 2019).

Crack detection relies heavily on image processing and machine learning (Liu and Yeoh, 2021; Li et al., 2017; Dung and Anh, 2019). The Convolutional Neural Network (CNN) is the most commonly used method (Cha et al., 2017). The Minimum Path Selection (MPS) is also found to provide robust and accurate crack segmentation within grey level images (Baltazart et al., 2017). The Deep Convolution Neural Network (DCNN) method—the network in transfer learning mode—accurately detected 86% of cracked images and could detect cracks coarser than 0.04 mm (Dorafshan et al., 2018). For characterizing the crack pattern for condition assessment from visible cracks, binary classification of crack patterns into isolated patterns and map patterns is proposed (Liu and Yeoh, 2021). To further reduce manual operation, an automatic surface crack detection robot is designed to capture the concrete surface by the sectoring method. The Haar trained cascade object detector classified surface crack by using both positive and negative samples (Balbin et al., 2017).

For crack measurement, 2D image processing and 3D point cloud reconstruction method are used to extract crack parameters that reflect the severity of cracks (Slonski and Tekieli, 2020; Wei et al., 2021b). Using Fusion Features-based Broad Learning System(FF-BLS)and image processing for crack measurement, the results show that compared with CNNs(Convolutional Neural Networks), FF-BLS achieved a similar level of recognition accuracy but the training speed was increased by more than 20 times (Zhang and Yuen, 2021).

Using the two-dimensional amplitude and phase estimation method, the effective identification rate of bridge cracks can reach 90.5% (Dan and Dan, 2021). The average deviations between the crack length and width observed by the crack viewer and calculated from the 3D point cloud data are 7.52% and −9.01%, respectively (Wei et al., 2021b). An image-based method is introduced to extract crack pattern characteristics, including crack width and length in crack monitoring of concrete bridges and tunnels (Asjodi et al., 2021). In addition, a combination of 2D and 3D is proposed, which the experiments shows that the results can achieve an absolute error of less than 0.08 mm and a relative error of less than 3% (Liu et al., 2016).

(2) Spalling

The spalling of the structural surface weakens the corrosion resistance and durability of the structure. The accuracy of results heavily relies on lighting conditions. Using piece-wise linear stochastic gradient descent logistic regression and image texture analysis can achieve good detection accuracy of concrete spalling, with a classification accuracy of 90.24% (Hoang et al., 2019). Image processing technology and support

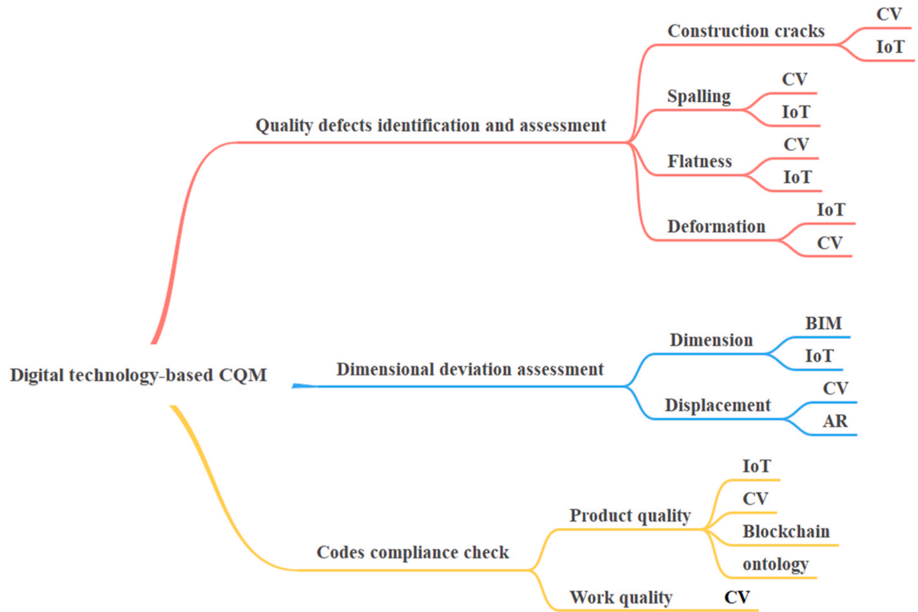

Fig. 4. Framework of digital technology application in CQM.

vector machines have been integrated for subway wall spalling, and the accuracy could be as high as 91.7% (Dawood et al., 2017). Ground laser scanner has also been used to locate and quantify spalling defects on concrete surfaces, but shallow spalling less than 3 mm deep cannot be identified yet (Li et al., 2021).

(3) Deformation

In terms of structural deformation monitoring, Global Navigation Satellite System (GNSS) monitoring technology has great potential in large-scale structural deformation monitoring, while research has been focused on hardware and algorithm development. Compared with traditional monitoring methods (i.e., accelerometers and displacement sensors), GNSS can provide real-time monitoring with higher accuracy (10–20 mm) and reliability (Yi et al., 2018; Yu et al., 2017). The combination of GPS and other GNSS constellations can improve the overall performance of the monitoring system. The multi-constellation GNSS can enhance satellite geometry and improve positioning accuracy by obtaining more accurate double differential measurements (Yu et al., 2020). Combined with machine vision, the accuracy of deformation detection is less than 0.12 mm in the tunnel project (Qiu et al., 2018).

Research on quality defect detection benefited and was restrained from the rapid development of laser scanning technology and image processing algorithm. On the one hand, most of these studies focus on surface quality evaluation, and few studies concentrate on the internal quality of concealed works. On the other hand, there is a lack of research on other general quality problems such as leakage, blockage, unreasonable spatial layout, etc.

4.2. Dimensional deviation assessment

The key quality control process is to examine the deviation between construction products and design parameters and control the deviation within the allowable specifications or codes. Research on construction deviation mainly focused on products dimension includes size (Wang et al., 2016), shape (Kim et al., 2016), position and orientation (Zhang et al., 2018a).

For digital deviation examination of site work, through experiments carried out using the cast-in-site concrete components, the accuracy is up to 97% (Maalek et al., 2019). Real-time automatic registration of video sequences to BIM is further proposed to monitor construction quality (Asadi et al., 2019) rapidly.

To project design intent on the construction site, AR is applied to connect the site status and visual model (Napolitano et al., 2019). AR can improve capturing of essential facilities' comprehensive, high-resolution, 3D measurements (Mascarenas et al., 2021). It has been applied to compare the field segment displacement (Zhou et al., 2017) with the baseline model to visually check on large deviations and missing architectural elements (Chalhoub et al., 2021).

4.3. Codes compliance check

Compliance checking provides the processes and results of whether construction complies with relevant laws, policies, and regulations.

For construction process check, to ensure the vibration quality of fresh concrete, a real-time monitoring framework is proposed based on fine-tuned ResNet-50 model and IoT technology with an average F1-score of 97.97% (Wang et al., 2021). Compared to the manual method, the biases of insertion depth and vibration duration are respectively within 2.75 cm and 3s, which verifies the high accuracy and reliability of monitoring results (Wang et al., 2021). Casing grouting is often used to connect prefabricated components and form key nodes. Using the sensor to obtain the density and mechanical performance data of grouting in the casing for quality detection can improve the detection efficiency and accuracy of the quality of prefabricated component nodes (Yao et al., 2021). Through the integration of textual data and sensing data, a construction procedural data integration framework is developed to conduct construction execution steps compliance checking automatically (Ren and Zhang, 2021).

For product compliance check with codes, to exam the thickness of the reinforcement covering layer, the diameter of reinforcement is estimated with electromagnetic induction, ground-penetrating radar and the maximum estimation error for the cover thickness does not exceed 6.7% (Zhou et al., 2018). Besides, sensor, sub-pixel boundary location method, and fast stitch method are used to obtain images and videos from the construction site to detect the diameter, spacing, and quantity of reinforcement with 0.002% error (Zhang et al., 2018b).

Research on automatic compliance inspection with specifications mainly focused on the design stage rather than the construction stage (Soliman-Junior et al., 2021; Gao et al., 2022). Rule terms are mapped to keywords (concepts or properties) in BIM data through term matching and semantic similarity analysis (Guo et al., 2021b). Automated regulatory compliance checking requires automated extraction of requirements from regulatory textual documents and their formalization in a computer-processable rule representation. To reduce the number of needed patterns for information processing, phrase structure grammar-based phrasal tags and sequencing of semantic information elements are proposed (Zhang and El-Gohary, 2016).

In addition to construction deviation control, a normative check of the construction process is also critical to ensure the quality of end products. By modeling the regulatory constraints as Object Windows Library (OWL) axioms and Semantic Web Rule Language (SWRL) rules (Zhong et al., 2012), the regulatory provisions for quality inspection can be transformed into a set of inspection checklists and associated with specific construction tasks. However, no tool can currently provide complete pre-inspection compliance capability before formal submission (Beach et al., 2020).

In general, construction quality research mainly focuses on obtaining detailed design information, acquisition and analysis of inspection data, and defect detection (Ma et al., 2018), but still faces following problems:

1. Lack of defects identification of concealed works other than surface quality assessment and measurement on concrete and steel.
2. Digital technology is mainly applied in the construction process. Thus, there is a lack of preventive control before construction and functional test runs for end products.
3. In addition to design deviation, little attention is paid to the compliance of construction quality specifications, especially work behavior.

5. Research and application challenges

5.1. Research challenges

(1) Data acquisition and processing

Quality data accuracy is hard to guarantee due to the data acquisition environment's complexities, acquisition equipment performance limitations, and human factors (Chen et al., 2017). The real-world data might contain irrelevant or meaningless data artifacts termed noise. Noise data is detrimental to almost any data analysis (Gupta and Gupta, 2019)]. It is difficult to guarantee data integrity because data might be lost or tampered with (Fan et al., 2021). Storage formats are diversified, semantic expressions vary from person to person, and numerical values are diverse, which may lead to data inconsistency (Shi et al., 2019).

Data sources are challenging to obtain as very few public data on construction quality are available. Contractors and owners hesitate or refuse to provide quality records with sensitive information that might compromise construction projects. Insufficient training samples might lead to poor interpretation of models in data analysis using deep learning (Xi and Zhao, 2019). Data augmentation is proposed to maximize the available data by providing additional data for limited training data with minor changes such as image rotation and flipping. However, data augmentation can also cause the potential loss of relevant data or outliers needed for training. A more comprehensive range of data in the construction industry is structured, and data augmentation for this data can be complicated (Akinosho et al., 2020).

Deep neural networks require massive input data, long-time training, and advanced configuration of hardware. Even so, the gradient dissipation and collapse problems are easy to occur in the process of model training (Ratcliff, 1990). Some researchers used CNN to classify construction complaint texts and found that the smaller the number of samples in grouping training, the worse the model performance (Zhong et al., 2019).

(2) Generalization ability of model and algorithm

Machine learning models can generally be divided into two categories: (1) shallow structure model and (2) deep structure model. The algorithm models of shallow structure include support vector machine, boosting, logistic regression, etc. Many experiments and pilot studies show that shallow structure model performs poorly for feature extraction in processing high-dimensional data such as images, video, voice, and natural language. While in discovering intricate structures in high-dimensional data, deep learning performs very well (LeCun et al., 2015), there are many shallow structure models for image-based concrete damage detection. However, they rely on low-level features and may not work effectively in practice (Jiang et al., 2021).

Shallow and deep structure networks have overfitting and poor generalization issues. The depth network contains more hyper-parameters than shallow network, which increases the probability of overfitting (Bejani and Ghatee, 2021). Overfitting and poor generalization reduce the model's prediction ability to unknown data. Overfitting may be caused by the noise of training samples, lack of training samples, biased or disproportionate training samples, non-negligible variance of the estimation errors (Cawley and Talbot, 2010), multiple patterns with different non-linearity levels that need different learning models (Caruana et al., 2001), biased predictions using different selections of variables, stopped training procedure before convergence or dropping in a local minimum (Srivastava et al., 2014), different distributions for training and testing samples, etc.

5.2. Application challenges

Research on digital technology in construction has been widely conducted, but there are still problems to be solved for the quality aspect. AR application faces latency problems. The time delay of virtual environment calculation will lead to the displacement between the real and virtual environments (Xu and Moreu, 2021). Recently, most AR devices use the laser to overlay virtual images in real environments. The laser works well and steadily in the indoor environment, while outdoor temperature and brightness will affect performance with dizziness and nausea.

Although machine vision has been widely introduced in research on surface quality, how to quickly and accurately identify targets and effectively construct reliable recognition algorithms remains to be further resolved.

Storage capacity and scalability have been deeply questioned in blockchain (Reyna et al., 2018). At present, Ethereum can only reach 7 transactions per second, which cannot meet the regular needs of work and production (Prewett et al., 2020). On the premise of ensuring credibility, blockchain technology faces scalability problems. If this problem is not solved, the transaction processing time may be longer and longer. The distributed, decentralized nature of blockchain "grants blockchain coders and developers' freedom" to tailor systems to the needs of specific users. A lack of standardization is detrimental to user communication (Behnke and Janssen, 2020).

6. Future research directions

Although substantial efforts are made for automated CQM, challenges on both research and application cannot be ignored. Based on the bibliometric analysis, a full review of related works, and challenges analysis, future research directions are proposed for better digital technology-based CQM.

6.1. Quality culture development

With the development of quality management theory, the objectives have moved from absolute zero defects (Psarommatis et al., 2022) to error prevention (Love et al., 2011). Although quality inspection of the end product is currently a significant strategy for error detection and prevention (Lin et al., 2016), the core of improving quality is a scientific, rigorous, and efficient quality system (Roderick, 1996) to establish an adequate quality culture.

Quality culture is a part of the organization culture and is situated in the organizational context (Ehlers, 2009). It reflects the general approach, the values, and the orientation to quality that permeate organizational actions (Cameron and Sine, 1999). Studies show that quality culture impacts quality performance (Corbett and Rastrick, 2000). Cameron et al. classify quality culture according to its development: the absence of emphasis on quality, error detection culture, error prevention culture, and creative quality culture (Cameron and Sine, 1999). One of the essential elements of quality culture is quality systems and rules such as total quality management. In addition, participation, trust, and communication are also crucial for a quality culture (Ehlers, 2009). Poor quality management perceptions in organizations and employment conditions for construction workers, and safety and schedule pressures have contributed to poor quality culture.

Quality culture focuses on organizations' cultural patterns, like rituals, beliefs, values, and everyday procedures, while following processes, rules, and regulations (Ehlers, 2009). It affects workers' and organizations' attitudes and behavior from the inside and incorporates quality as a characteristic of organizational culture. For workers, the pursuit of quality culture is manifested to a large extent through sound knowledge of duties, the ability to improve skills, and total commitment to the performance of one's duties. Workers are encouraged to upgrade their qualifications while increasing the strength of their actual influence on colleagues (Pietruszka-Ortyl, 2019).

An overriding assumption is that construction errors can be prevented; in practice, people are blamed for their errors. Errors are not random acts but are systematically connected to aspects of people's tools, tasks, and work environment (Love, 2020). If a person perceives an error involving more potential punishment than benefits, they are more likely to hide them (Love et al., 2019a). Also, senior management is often reluctant to hear 'bad news', which are interpreted as poor management and deny the existence of quality problem (Love, 2020). Consequently, an error prevention culture encumbers workers' positive engagement in construction quality and stifles the ability to innovate and learn from error (Love et al., 2019b; Love and Smith, 2016). Once an error-mastery culture is established in construction organizations, they will be better positioned to realize the benefits of the techniques, tools, and technologies espoused to address rework (Love et al., 2022).

There have been studies on AR or VR-based employee skill enhancement (Osti et al., 2021; Bosché et al., 2016), and the establishment of individual and organizational reputation mechanisms based on blockchain (Qian and Papadonikolaki, 2021; Zhang et al., 2019). But there is still an absence of research on digital technology-based quality culture, such as rework and error management. Therefore, one future research direction is how to apply digital technology to construction quality culture and improve the existing quality culture.

6.2. Advanced data analytics

Data analytics capabilities are a key theme in many digital technologies. Constantly optimized data analysis capabilities provide more robust methods to solve complex and large-scale problems. For example, the algorithms and models used for construction quality defect identification discussed in the previous section are constantly upgraded to obtain better defect identification results. Since the data acquired by sensors as well as IoT, etc. Are large and prone to noise, incompleteness, and inconsistencies, the analysis of such large amounts of data requires advanced analytical techniques to effectively review or predict future courses of action with high accuracy and advanced decision-making strategies (Hariri et al., 2019).

Improving data, algorithms, or models are beneficial to optimizing data analysis. Model faces problems with data fusion and model updating. Presently, deep learning is used for data fusion. The basic principle of multi-source and multi-modal deep learning fusion is the same as that of classical deep learning, but the datasets used for learning and training are different, from single data to multi-source and multi-modal datasets, or cross-use of datasets with different modes. However, data fusion may lead to an "exponential explosion" in the amount of computation.

In summary, applying advanced data analysis methods to more construction scenarios or optimizing the efficiency and accuracy of existing CQM data analysis can help improve construction quality.

6.3. Behavioral quality assessment

Amongst the construction product quality data analysis, the quality defects in construction products can be identified in time with corrective measures. The focus of quality management is gradually shifting from post-control to in-process control and pre-control. Workers are the ultimate executors of the engineering plan. They decide how the construction process will be implemented, which is reflected in their behavior (Závadský et al., 2020). Factors such as workers' motivation, awareness, attitude, emotion, and ability will determine their behavior and affect the quality of the product.

If work quality meets standards or specifications in each process, there is a high probability that the final product will meet the standards. Error operation by workers is the leading cause of quality problems (Rejeki et al., 2020). NLP can be used to parse the regulation provision from text into OWL axioms and SWRL rules and check semantic behavior for specific construction tasks. Through tracking and analyzing workers' behavior onsite, the compliance inspection of the construction process can be automatically accomplished in time with corrective measures.

7. Conclusion

This study aimed to elucidate the state-of-the-art review of digital technologies for the CQM. A total of 108 articles were collected from international journals and keyword searches from Web of Science database. The results confirm that the current research lacks the quality management of concealed works, and effective process control on compliance check. Also, it is difficult to obtain quality data to perform thorough evaluation. For application, digital technologies also face personal privacy, security, and cost-effective challenges. Therefore, future research studies are warranted to consider quality culture, data processing algorithm, and behavioral quality to obtain and carry out comprehensive real-time CQM. This paper provides an essential reference for practitioners studying digital technology-based CQM. This review makes contributions by revealing the state-of-the-art algorithms and techniques for the CQM.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Hanbin Luo reports financial support was provided by National Natural Science Foundation of China.

Acknowledgement

The authors would like to acknowledge the financial support provided by the National Natural Science Foundation of China (Grant No. U21A20151, 51978302).

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